Essays on Return Predictability

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A dissertation submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy in Finance

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Massey University

10 July 2013

Acknowledgements

I greatly acknowledge the advice, encouragement and support of my supervisors, Ben Jacobsen, Philip Stork and Russell Gregory-Allen. I thank the department of Economics and Finance for providing financial support and an inspiring research environment.

Abstract

This dissertation is a collection of three essays that investigate the momentum effect and the short-run predictability in currency carry trade profits.

The first essay investigates whether tail risks of momentum strategies make them unattractive within the context of prospect utility. Momentum returns have strongly asymmetric tail risks and that asymmetric tail risk is precisely what makes momentum strategies unattractive. This study is the first to document the undesirable tail risk characteristics of momentum returns.

The second essay uncovers economically significant predictability in carry trade profits from shorting the low-yielding currencies. The monthly world equity index return, monthly changes in currency volatility and monthly changes in equity volatility predict carry trade profits from the short leg two months later, while monthly changes in commodity prices, monthly changes in currency volatility and monthly changes in equity volatility predict carry trade profits from the long leg three months later. Investors could have used the discovered leg-specific predictability to time the market and improve their trading outcomes, instead of staying fully invested or predicting carry trade profits from both legs with a single model. Evidence from two tests conducted in this essay points towards the gradual information diffusion model as the most likely explanation for the discovered predictability, while time-varying risk premia do not seem to explain this effect.

The last essay examines return predictability among carry trades, stocks and commodities in a dynamic vector autoregression setting. The predictive effect goes from commodities to stock, from stocks to low-yielding currencies and from commodities to high-yielding currencies. Variables in these markets are more strongly correlated in the high-risk regime than in the low-risk regime. Drops in the world equity index (commodity prices), but not rises, predict decreases in carry trade profits from low-yielding (high-yielding) currencies. Increases in currency volatility, but not decreases, predict drops in carry trade profits from low-yielding currencies. The in-

sample asymmetric effects also exist out-of-sample, but these asymmetric prediction models do not consistently deliver better forecasts than symmetric models.

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Chapter 1 Overview

This dissertation is a collection of three essays that investigate the short-run predictability in stock returns and short-run predictability in currency carry trade profits. I consider three different angles: tail risks of stock momentum returns; predictability in currency carry trade profits and possible explanations; and return predictability among carry trades, stocks and commodities.

We have known for decades that stock returns are predictable over business cycles (Cochrane, 2005). For example, slowing-moving variables such as dividend/price ratio and term premium predict stock returns particularly well at horizons longer than one year (Fama and French, 1989). While long-run predictability in stock returns is well established, until recently we have not had convincing evidence for short-run stock predictability. The essays in this thesis investigate two phenomena related to short-run return predictability: the momentum anomaly and carry trades.

The first essay is related to the tail risk of momentum strategies. The stock momentum anomaly rests on a simple form of return predictability – it relies on the weak predictability in stock returns from their past returns. This short-run predictability is weak at the individual stock level; however, it can be amplified by dynamic rebalancing momentum strategies. As shown in the seminal work by Jegadeesh and Titman (1993, 2001), momentum strategies earn large excess returns that cannot be explained by common risk factors. The persistence of momentum profits suggests that past returns contain useful information for future returns. Since Jegadeesh and Titman's work, momentum has become the most studied anomaly. Numerous studies have put forward various behavioural and risk explanations for the momentum effect. My first essay is most closely related to the work by Menkhoff and Schmeling (2006), who show that, if investors have prospective preferences, or care about extreme outcomes instead of just the mean and variance (or, behave more like "normal people"[1]), they will prefer buy-and-hold strategies to momentum strategies. Taking their work one step further, I investigate what makes momentum strategies unattractive within the context of prospect utility. I show that momentum returns have strongly asymmetric tail risks and that this asymmetric tail risk is precisely what makes momentum strategies unattractive. The main contribution of this essay is that it is the first study to document the undesirable tail risk characteristics of momentum returns.

The second essay turns to another financial market anomaly – profitability of carry trades. Bakshi and Panayotov (2012) are the first to thoroughly investigate the short-run predictability in dynamic carry trade profits. They show that commodity price changes and currency volatility changes strongly predict dynamic carry trade profits, both in-sample and out-of-sample. This second essay contributes to the carry trade return predictability literature in two respects. *First*, it uncovers economically significant short-run predictability in carry trade profits from low-yielding currencies. Monthly world equity index returns, monthly changes in equity volatility and monthly changes in currency volatility predict profits from shorting the low-yielding currencies two months later, while monthly changes in commodity prices, monthly changes in equity volatility and monthly changes in currency volatility predict profits from longing the high-yielding currencies three months later. This leg-specific predictability could have helped investors to further improve their trading outcomes, as compared with using a single model to predict long/short carry trade profits from both legs. *Then*, I conduct two tests to show that the discussed predictability in carry trade profits is consistent with the hypothesis that information related to economic fundamentals gradually flows from commodity markets to high-yielding currencies and from equity markets to low-yielding currencies. The first test, following Driesprong, Jacobsen and Matt (2008), shows that predictive effects in carry trade

[1] Prospect utility (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) is the most successful utility function in describing people's real-life choices.

profits strengthen, peak and quickly drop as the lag between predictors and carry trade profits lengthens. The second test, following Hong, Torus and Valkanov (200), shows that a variable's ability in predicting carry trade profits is strongly and positively correlated with its ability in forecasting the OECD industrial production growth. While I acknowledge there are other possible explanations for the discovered predictability, the findings in this essay suggest that the predictability in carry trade profits may be related to predictors' propensity to forecast economic fundamentals. Results from these two tests suggest that the gradual information diffusion hypothesis, put forward by Hong and Stein, 1999, and Hong, Torous and Valkanov, 2007, is the most likely explanation for the discussed predictability in carry trades.

While results from the second essay suggest that predictive effects go from commodities to currencies and from stocks to currencies, the lead-lag effects can also go the other way around, from currencies to stocks and from commodities to currencies (for example, Chen, Rogoff and Rossi, 2010; Granger, Huangb and Yang, 2000). Building on the results from the second essay, the third essay investigates return predictability among three types of assets, namely, the carry trades, the MSCI world equity portfolio and the CRB Raw Industrial Commodity Index. This essay has two interesting findings. *First,* using vector autoregressive models, I find that the predictive effects are from commodities to high-yielding currencies, from commodities to the world equity index and from the world equity index to low-yielding currencies. *Second*, many of the predictive effects, as well as contemporaneous correlations, are asymmetric. Drops in the world equity index, decreases in commodity prices and carry trade losses are more correlated than their upside movements. Correlations between negative returns from these three assets and increases in either equity volatility or currency volatility are also higher than those between increases in prices and drops in volatility. In the sample, drops, but not rises, in the world equity index return two months ago predict decreases in carry trade profits from low-yielding currencies in this month. Similarly, decreases, but not increases, in commodity prices three months before significantly predict drops in carry trade profits from high-yielding currencies in this month. Changes in currency volatility also exhibit asymmetric effects on future profits from the short leg of carry trades – only increases in currency volatility significantly predict the short-leg profits in two months' time. In contrast, changes in equity volatility do not demonstrate asymmetric effects on future carry trade profits. Rises and drops in equity volatility do not have significantly different slope estimates when they are used to predict carry trade profits. These in-sample significant asymmetric effects are stable across time and deliver good out-of-sample performance, when benchmarked against historical mean models. However, these asymmetric predictions models do not have significantly better out-of-sample performance than the symmetric prediction models investigated in the second essay.

Chapter 2 Asymmetric Extreme Tails and Prospective Utility of Momentum Returns[1]

Abstract

This essay uses extreme value theory to analyse the tails of a momentum strategy's return distribution. The asymmetry between the fat left tail and thin right tail strongly reduces a momentum strategy's prospective utility levels.

JEL Classification: G11, G12, G14

Keywords: Extreme value theory; Asymmetric tails; Prospective utility

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[1] This chapter is based on a published paper I co-authored with Professor Philip Stork and Associate Professor Russell Gregory-Allen. Our paper is titled "Asymmetric Extreme Tails and Prospective Utility of Momentum Returns" and is published in *Economics Letters* 117 (1), 295–297.

1. Introduction

Momentum is a dynamic equity investment strategy that buys past winners and shorts past losers. This simple strategy can make abnormal returns that cannot be explained by conventional asset pricing models (CAPM and Fama-French Three Factor Model). The persistence and prevalence of abnormal momentum returns are puzzling.

Menkhoff and Schmeling (2006) show that prospect theory provides a possible explanation for the puzzling high momentum returns. Their study suggests that momentum may not be truly anomalous if an investor cares more about extreme losses than other outcomes (or has *a prospective utility*). If the investor has a prospective utility, he could be better off simply holding the equity market index portfolio instead of pursuing momentum strategies. Their findings also imply that momentum strategies may generate more extreme losses and gains than a buy-and-hold strategy. Motivated by the findings of Menkhoff and Schmeling (2006), this essay investigates whether tail risk makes momentum strategies undesirable for prospective investors.

The distinguishing factor of the analysis in this essay is that it focuses on the extreme tails of the momentum return distribution. To the best of my knowledge, this study is the first to analyse the tail risks of a momentum strategy. This study finds that momentum returns have asymmetric tail risks. It is precisely this tail asymmetry that makes a momentum strategy less attractive than a market strategy for a prospective investor.

2. Related literature

This essay is related to three strands of literature, namely, momentum anomaly, extreme value theory and prospect theory.

2.1. Momentum anomaly

Momentum is one of the most studied anomalies. Momentum literature can be categorized into three groups: the wide existence of momentum profits, risks of momentum strategies and behavioural models which could offer explanations for momentum profits.

The first group of literature provides evidence on the persistence and prevalence of momentum profits. Momentum profits exist over time, across countries and across asset classes. Jegadeesh and Titman (1993 and 2001) document that a strategy which selects stocks based on their past six-month returns and holds them for six months realizes a compounded excess returns of 12.01% per year on average over the 1965 to 1989 period, and that the momentum profits in the eight years subsequent to the sample period in the 1993 paper are remarkably similar to the profits found in the earlier time period. These excess returns are unexplained by CAPM or the Fama-French three-factor model. Griffin et al. (2005) find that both price and earning momentum strategies yield statistically significant and economically high profits in 40 stock markets globally. Okunev and White (2003) document that momentum profitability continued to exist in the 1990s in foreign exchange markets. Miffre and Rallis (2007) reveal 13 profitable momentum trading strategies in commodity future markets.

Momentum strategies involve frequent re-balancing of portfolios. Are they still profitable after transaction costs? Lesmond et al. (2004) argue that momentum profits are merely a compensation for trading cost and hence are illusory. However, many studies document profitable momentum strategies which are robust to transaction costs; for example, industry momentum strategy (Moskowitz and Grinblatt, 1999), style momentum strategy (Chen and De Bondt, 2004), liquidity-based and value-based momentum strategy (Korajczyk and Sadka 2004) and momentum strategies conditioned on trading volume (Lee and Swaminathan, 2000).

The second group of literature attempts to explain the source momentum profits by priced risk factors. Momentum profits have been related to systematic skewness, business cycle, time-varying expected dividend growth, liquidity risk, credit risk, time-varying macro-economic risk and time-varying unsystematic risk. Harvey and Siddique (2000) document that momentum returns are very negatively skewed. Akhtar, Chordia and Shivakumar (2002) and Cooper, Gutierrez and Hameed (2004) find that momentum profits are strong in economic expansions but are nonexistent in recessions. Johnson (2002) proposes a model with varying expected dividend growth in which momentum effects need not imply investor irrationality. Pastor and Stambaugh (2003) uncover that a liquidity risk factor accounts for half of momentum profits. Avramov et al. (2007) show that momentum profits are large and significant among firms with low-grade credit ratings but are non-existent among firms with high-grade credit ratings. Liu and Zhang (2008) incorporate time-varying macro-economic risk factors (industrial Growth) in the traditional Fama-French three-factor model and explain approximately half of momentum profits. Li et al. (2008) find that unsystematic risk can partially explain momentum profit.

The last group of literature has attempted to explain momentum profits by behavioural models such as conservatism, overconfidence, slow information diffusion and investors' prospect preference. Barberis, Shleifer and Vishny (1998) and Daniel, Hirshleifer and Subrahmanyam (1998) both present models of investors' under- and over-reactions that provide possible explanations for momentum effect. Hong and Stein (1999) and Hong, Lim and Stein (2000) resort to bounded rationality and the gradual flow of information across markets to explain momentum effect. Jiang, Lee and Zhang (2005) and Zhang (2006) report that momentum profits are higher among firms with higher information uncertainty that can be measured by size, age, return volatility, cash flow volatility and analyst forecast dispersion. Finally, Menkhoff and Schmeling (2006) document that investors with prospect preference and a short investment evaluation horizon will not implement a momentum strategy because it offers lower utility than the utility from a strategy that borrows at risk-free rates to invest in the market portfolio.

Among the voluminous literature on momentum effect, this essay is most closely related to the work by Menkhoff and Schmeling (2006). This essay provides further insight into the explanation put forward by Menkhoff and Schmeling (2006) for the momentum effect. Menkhoff and Schmeling (2006) demonstrate that momentum strategies offer lower prospective utility than the buy-and-hold strategy. This essay complements their work by showing that the asymmetric tail risks are precisely what make momentum strategies undesirable for prospective investors.

2.2. Extreme value theory

This essay is also related to the literature that applies the extreme value theory to capital markets and asset pricing. Previous well-known studies that apply extreme value theory in the areas of capital market and asset pricing include Hartmann and de Vries (2004), Straetmans et al. (2008), Bollerslev and Todorov (2011), Kelly (2009), and Pais and Stork (2010). Hartmann and de Vries (2004), Straetmans et al. (2008) and Pais and Stork (2010) apply extreme value theory to test extreme co-movements among asset markets. Bollerslev and Todorov (2011) and Kelly (2009) show that tail risk is a priced risk factor. This essay examines the extreme tail risks of momentum effect and is the first to apply extreme value theory to momentum anomaly. Using the Hill estimator (1975),[2] it is possible to examine the extreme left tail risk and the extreme right tail risk of momentum anomaly separately and uncover that moment effects have undesirable asymmetric tail risks.

2.3. Prospect theory

Will an investor be concerned about such asymmetric tail risks of momentum returns? Almost tautologically, a mean-variance investor will not consider tail risks in addition to mean and variance. That is, a mean-variance investor will prefer momentum strategies to a buy-and-hold strategy, as long as the momentum strategy generates a higher average return and lower variance than the buy-and-hold strategy. Quite contrary to the underlying utility assumptions of mean-variance investors, this essay takes the position of investors who dislike losses and do care about extreme outcomes. We dislike losses – dis-utility from a loss cannot be compensated by a gain of similar size. Also, we care more about the extreme outcomes than other more common outcomes; hence, we are willing to "over-pay" (as compared with the probability-weighted payoff) for both insurance and lottery. When we make decisions, we behave like prospective investors described by the prospect theory developed by the Nobel Laureates Kahneman and Tversky (1979, 1992). Thus, in order to assess

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[2] A brief summary of the Hill estimator (1975) is provided in Section 4.1.

how tail risks affect investor choices, this essay assumes that investors have prospect preference and follows the approach taken by Benartzi and Thaler (1995) to compute prospective utility levels.

3. Data

This essay takes the perspective of a U.S. investor and examines the tail risks of equity momentum strategies in the U.S. stock market. Monthly momentum returns are computed using total returns of all shares listed on the NYSE, AMEX and NASDAQ from the Chicago Booth Center for Research in Security Prices (CRSP), from December 1926 to December 2009. I examine the tail risks of momentum returns and their impact on prospective utility. The main results in this essay are generated from monthly returns of an overlapping 6/6 strategy, which is identical to that used in Jegadeesh and Titman (2001).[3] In order to be assured that my results are not specific to one momentum strategy or only monthly returns, I also examine tail risks of other momentum strategies and daily momentum returns. These additional results are reported in the section titled “robustness tests” .

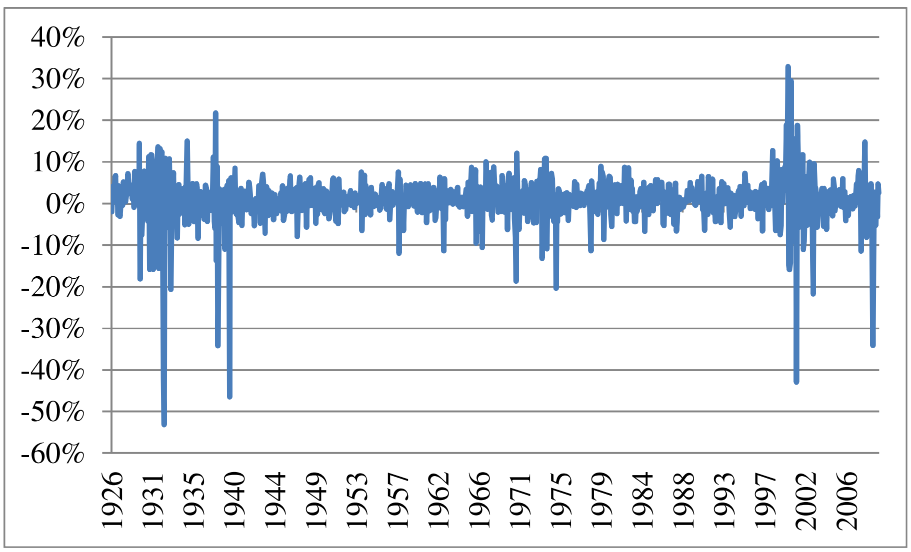
Following Jegadeesh and Titman (2001), I use an equal-weighted overlapping 6/6 strategy, where at the beginning of each month, stocks are ranked based on the past six months’ returns. Stocks priced less than US$5 at the beginning of the holding period and stocks in the smallest market capitalization decile (NYSE size decile cutoff) are excluded from ranking because it is difficult to short-sell illiquid stocks. The top performance decile (winners, P1) will be held for six months. The worst performance decile (losers, P10) will be shorted for six months. One-sixth of the portfolio is rebalanced at the beginning of each month. Momentum returns are computed as returns from holding the winners’ portfolio and shorting the losers’ portfolio (WML, P1-10).

[3] 6/6 refers to the six-month formation period and six-month holding period. I have replicated the momentum profits in Jegadeesh and Titman (2001) and obtain identical results.

Figure 2.1 depicts monthly WML (P1-10) portfolio returns from December 1926 to December 2009. The plot in Figure 2.1 reveals that the momentum strategy generates many very large extreme losses. For example, in early 2000, a momentum investor could have lost more than half of his or her portfolio value. These extreme losses motivate my investigation of momentum tail risks. Are left tail risks and right tail risks of the same scale? How do tail risk characteristics of momentum strategies affect prospect investors? My essay attempts to answer these two questions. Before presenting the main results in Section 5, I first briefly summarize in Section 4 the main methodologies applied in this essay.

Figure 2.1 WML monthly returns

This figure plots the monthly return from an overlapping 6/6 momentum strategy (identical to that used in Jegadeesh and Titman, 2001) across the sample period starting December 1926 and ending December 2009.



4. Methodologies

4.1. Hill estimator, Value at Risk (VaR) and expected shortfall

As the return distribution has fatter tails than a normal distribution, I use a power law distribution to fit the tails in order to estimate the extreme event risk. Tail risk estimates based on normal distribution tend to severely under-estimate the extreme risk. One can choose to assess the fatness of tails by kurtosis. However, kurtosis only captures the probability mass of the distribution at the centre relative to the tails, instead of directly measuring the fatness of tails. For example, it is easy to construct a distribution with truncated tails, and thin tails, which exhibits high kurtosis. Neither does kurtosis allow the assessment of the fatness of the left tail and that of the right tail separately. Thus, one can approximate the tail probability distribution function by the Pareto distribution. Pareto distribution is a power law probability distribution. Let α be the shape parameter, the function F below is the distribution function:

$$\boldsymbol{F(x) = 1 - \frac{1}{x^{\alpha}},\ 1 \leq x < \infty} \tag{1}$$

The probability density function f is given by

$$\boldsymbol{f(x) = \frac{\alpha}{x^{\alpha+1}}, 1 \leq x < \infty}\ . \tag{2}$$

The tail index parameter α (γ=1/ α is called tail shape) measures how fat the tail of the return distribution is; a low (high) tail index means that the tail is fat (thin). Its value $\hat{\alpha}$ is estimated using the Hill (1975) method. Only values less than (left tail), or greater than (right tail), the cut-off value X_k are used to calculate the Hill estimator:

$$\hat{\gamma} = \frac{1}{\hat{\alpha}} = \left[\frac{1}{k}\sum_{j=1}^{k}\ln\left(\frac{x_j}{x_{k+1}}\right)\right], \tag{3}$$

where X is ranked in ascending order, with X_1 being the lowest return.

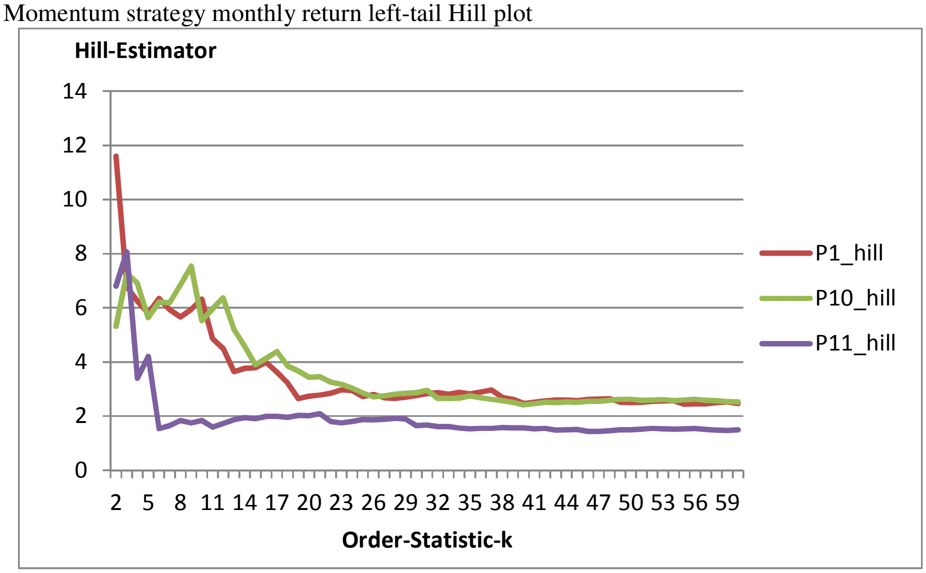
The choice of k requires a sufficient number of tail observations available to ensure lower uncertainty for the estimate, as well as further moving out into the tails for the Pareto distribution to ensure a better approximation for the tail distribution.

Following Slijkerman et al. (2005, p. 29) and Straetmans et al. (2008), I construct Hill plots for all return series, in order to determine the optimal level of k. The Hill plots show the relation between the number of order statistics used (k), and the tail index estimate $\hat{\alpha}$ (k). As an illustration, a sample of two Hill plots is included in Figure 2.1. The further one moves out into the tails, the better the Pareto approximation of these tails becomes. As a counterforce, the estimate begins to be based on fewer observations and, thus, becomes more uncertain. If the number of observations is increased by too much, the statistical power increases, but the estimate of the tail becomes distorted. In practice, a balance between the two opposing effects needs to be struck. Visual inspection of the Hill plots is needed to determine a range for k where $\hat{\alpha}\ (k)$ tends to be constant. For the full sample period, I set the number of order statistics used equal to 25 for momentum returns and 15 for market returns, as the Hill estimators are relatively stable at these levels. This threshold level is comparable to the threshold level used by Poon et al. (2004, p. 593).

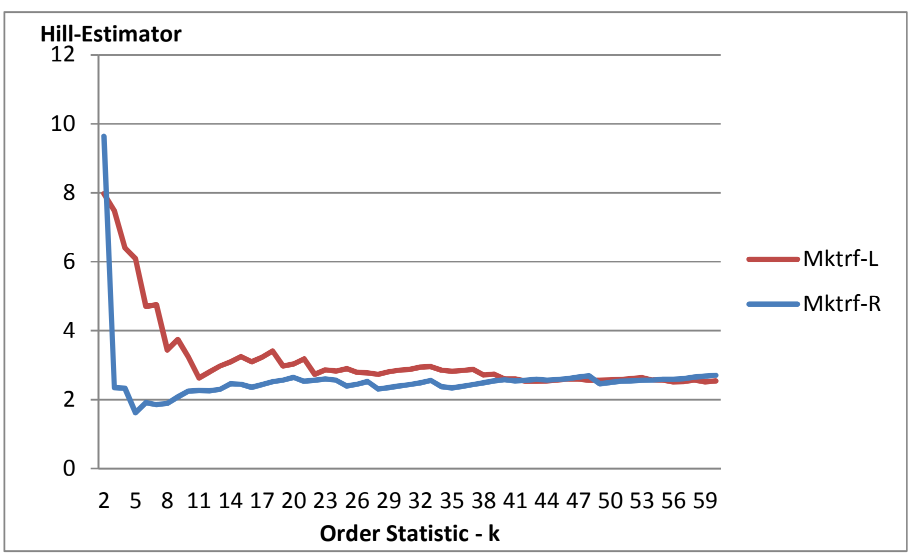
Figure 2.1 Hill plots

This figure plots the Hill estimator as the function of order statistic k.

A. Momentum strategy monthly return left-tail Hill plot



B. Market portfolio monthly return Hill plot



Although the α-estimate reflects the shape of the tail of the distribution, a VaR measure is needed for the downside risk. VaR is a standard measure of risk used for risk management by banks. It measures the possible maximum loss over a given holding period within a fixed confidence level. VaR is quoted in terms of a fixed time horizon h and a percentage α. If the VaR for a given (h, α) is V, then the loss over a horizon h should be less than V in α % of cases. For example, if the 99% one-day VaR is \$1 million, then the portfolio loss should be less than \$1 million on 99% of days. I employ the semi-parametric procedure from de Haan et al. (1994) to calculate the VaR. I refer to Novak and Beirlant (2006) for a recent application of an extreme value theory–based VaR estimator. More recently, Straetmans et al. (2008) also use a semi-parametric downside risk estimator.

The VaR is estimated as follows:

$$VaR_{p,N} = X_{k+1}\left(\frac{k}{Tp}\right)^{1/\hat{\alpha}} \tag{4}$$

N −period VaR is estimated as follows:

$$VaR_{p,N} = X_{k+1}\left(\frac{kN}{Tp}\right)^{1/\hat{\alpha}}, \tag{5}$$

where p =probability (that is, 1% for a once-in-a-hundred-day event for daily frequency data; 1% for a once-in-a-hundred-month event for monthly frequency data); and T= total number of observations.

VaR alone cannot, however, give us a full picture of the tail risk. These estimates indicate nothing regarding what to expect on the bad days when VaR is exceeded. Expected shortfall takes into account losses beyond the VaR level. It indicates the probability weighted average of the outcomes on the tail. Following Pais and Stork (2010), expected shortfall can be calculated as:

$$ES_{p,N} = \frac{\hat{\alpha}}{\hat{\alpha}-1} * VaR_{p,N} \tag{6}$$

4.2. Statistical tests for tail asymmetry

Hill (1975) proves that the statistic $\sqrt{k}(\hat{\gamma}(k) - \gamma)$ is asymptotically normally distributed $N(0, \gamma^2)$. Hence, following Hartmann et al. (2004, p. 317), a t-statistic is derived:

$$T = \frac{\hat{\gamma}_1(k_1) - \hat{\gamma}_2(k_2)}{\sigma[\hat{\gamma}_1(k_1) - \hat{\gamma}_2(k_2)]} \sim N(0,1) \tag{7}$$

In Equation (7), parameter k_i denotes the number of order statistics of return i that are used to estimate tail shape parameter $\hat{\gamma}_i(k_i)$. The denominator's standard deviation is calculated as the bootstrapped difference $\widehat{\gamma_1} - \widehat{\gamma_2}$. I opt for bootstrapping in blocks to preserve the nonlinear dependencies that might be present in the return data. Following Hartmann et al. (2004), I set the number of block bootstraps equal to 600. The optimal block length is fixed at the total number of observations raised to the power of 1/3, following Hall et al. (1995). The t-statistic may, for instance, be used to test for equality of the left and right tail index estimates (asymmetry test).

4.3. Moving block bootstrapping for dependent data

Bootstrapping allows estimation of the sampling distribution of almost any statistic using only very simple methods. This technique is suitable for situations where the theoretical distribution of a statistic of interest has no closed-form mathematical solution. Using bootstrapping, one draws observations randomly from a data series for a number of times till a new data series is generated; this procedure is repeated for N times, in order to obtain different realizations of time series. Then, the statistic of interest is calculated on different realizations. In this way, one obtains a distribution of the statistic of interest.

For time series data that are weakly dependent, one needs to use block bootstrapping, in order to preserve the autocorrelation presented in the data. In a block bootstrapping, data are divided into blocks and those blocks, instead of individual data points, are re-sampled. A question related to block bootstrapping is the choice of optimal block size. As demonstrated in Hall et al. (1995), the optimal block size for variance estimation of autocorrelated time series is $N^{1/3}$, where N is the total number of observations. This essay follows this simple rule suggested by Hall et al. (1995) and applied in many empirical studies (for example, Hartmann et al., 2004, Beber et al., 2011).

4.4. Simulations to generate momentum return prospects

Momentum returns generated from historical data have been used to simulate the expected return prospect, based on Benartzi and Thaler (1995). I randomly draw from historical monthly return data to simulate 100,000 returns in order to calculate the mean of each percentile and create percentile intervals. These intervals are then used as inputs in deriving prospective utility. First, distributions of returns are generated for one-month to 60-month investment evaluation horizons by randomly drawing 100,000 n-month consecutive returns from historical returns. Second, the 100,000 returns are ranked and averages are computed for each 0.5 percentile of 500 observations. Thus, the simulated returns are computed at 200 intervals along the cumulative distribution.

The prospective value function, as proposed and estimated by Kahneman and Tversky (1979) and Tversky and Kahneman (1992), has the following form:

$$v(x) = \begin{cases} x^{\alpha} & if\ x \geq 0 \\ -\lambda(-x)^{\beta} & if\ x < 0 \end{cases}, \tag{8}$$

where v is the value function; x denotes returns; and λ is the coefficient of loss aversion, which Tversky and Kahneman (1992) estimate to be 2.25. The estimated values for α and β are both 0.88, creating a concave shape in the domain of gains and a convex shape for the value function in the domain of losses. This procedure models agents as risk-averse for positive outcomes and risk-seeking for negative outcomes, relative to the reference point. Since the coefficient of loss aversion is larger than one, agents put more weight on losses than on gains of the same size.

The prospective utility is just the weighted sum of these values:

$$V(G) = \sum_i \pi_i v(x_i), \tag{9}$$

where π_i is a transformation of the probability p_i obtaining the i^{th} outcome. In cumulative prospect utility, this transformation depends not only on p_i, but also on the probabilities of the other outcomes. Specifically, π_i can be computed by taking the difference of the weighted probability of obtaining an outcome at least as good as the x_i (denoted P_i) and the weighted probability of obtaining an outcome that is better than x_i (denoted P_i^*), formally:

$$\pi_i = w(P_i) - w(P_i^*) \tag{10}$$

Under cumulative prospective theory (Tversky and Kahneman, 1992), people transform objective utility into subjective utility to value the prospect of gains and losses. The result of the weighing function is overweighting of the tails of the distribution. The parameter of this weighting function is estimated through experiments on people's attitudes towards risks. The weight w is

$$w(p) = \frac{p^\gamma}{(p^\gamma + (1-p)^\gamma)^{1/\gamma}}, \tag{11}$$

with an estimated value for γ of 0.61 and 0.69 for the domains of gains and losses, respectively.

5. Main results

Table 2.1 presents the summary statistics of monthly returns of the winner portfolio, the loser portfolio and the winner-minus-loser (WML) portfolio from the overlapping 6/6 momentum strategy and the summary statistics of returns from a buy-and-hold strategy (a "market strategy"). A momentum investor could have realized an average monthly profit of 0.89% from December 1926 to December 2009. This average return is noticeably higher than the 0.61% average monthly return from a buy-and-hold strategy. In addition, higher returns from the momentum strategy are not a mere compensation for higher volatility. Thus, the momentum strategy has a Sharpe ratio of 0.53, which is higher than the Sharpe ratio of a market strategy (0.39). Momentum strategies appear to be more attractive based on mean and variance.

Table 2.1 Summary statistics of momentum returns

This table presents the summary statistics of monthly returns from an overlapping 6/6 momentum strategy (identical to that used in Jegadeesh and Titman, 2001) and monthly returns from a market strategy for the period starting December 1926 and ending December 2009. The winner portfolio consists of top-decile past six-month winners. The loser portfolio consists of bottom-decile past six-month losers. In each month, one-sixth of the portfolio is rebalanced. The WML return is return from a strategy that longs winners and shorts losers. The market strategy buys and holds the value-weighted equity market portfolio. Excess returns from a market strategy refer to total returns in excess of the U.S. risk-free rates. Monthly risk-free rates and market portfolio returns are sourced from the Kenneth French website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

		Winners	Losers	WML	Market (excess return)
Returns	Minimum	-32.60%	-39.30%	-53.17%	-29.04%
	Maximum	43.54%	78.20%	32.91%	38.27%
	Mean	1.50%	0.61%	0.89%	0.61%
	St. dev.	7.32%	9.25%	5.84%	5.47%
	Sharpe ratio (annualized)	0.71	0.23	0.53	0.39
	Skew	-0.33	1.32	-2.53	0.17
	Kurtosis	3.72	11.41	21.50	7.56
	$\hat{\alpha}$-Left	2.72	2.85	1.87	3.24
	$\hat{\alpha}$-Right	2.95	1.91	3.58	2.45
	$\hat{\alpha}$- (Left-Right)	-0.23	0.95	-1.71	0.79
	t-stat	-5.905	33.515	-30.507	9.869
	p −value (2-sided)	<0.001	<0.001	<0.001	<0.001
Expected Shortfall	Left (5.0%)	-17.29%	-20.57%	-16.92%	-13.12%
	Right (5.0%)	15.82%	25.78%	12.19%	12.16%
	Left+Right(5.0%)	-1.48%	5.20%	-4.73%	-0.95%
	t-stat	-20.241	7.293	-11.998	-22.850
	p-value (2-side)	<0.001	<0.001	<0.001	<0.001
	Left (2.5%)	-22.31%	-26.23%	-24.53%	-16.25%
	Right (2.5%)	20.00%	37.06%	14.80%	16.15%
	Left+Right(2.5%)	-2.31%	10.83%	-9.73%	-0.10%
	t-stat	-20.355	7.744	-10.788	-22.814
	p −value (2-sided)	<0.001	<0.001	<0.001	<0.001
	Left (1.0%)	-31.24%	-36.16%	-40.09%	-21.56%
	Right (1.0%)	27.28%	59.88%	19.12%	23.49%
	Left+Right(1.0%)	-3.96%	23.72%	-20.97%	1.93%
	t-stat	-20.366	8.295	-9.080	-22.686
	p −value (2-sided)	<0.001	<0.001	<0.001	<0.001
	Left (0.5%)	-40.31%	-46.09%	-58.13%	-26.71%
	Right (0.5%)	34.50%	86.09%	23.21%	31.19%
	Left+Right(0.5%)	-5.81%	40.00%	-34.92%	4.48%
	t-stat	-20.266	8.672	-7.771	-22.528
	p −value (2-sided)	<0.001	<0.001	<0.001	<0.001

The kurtosis presented in this table is excess kurtosis. $\hat{\alpha}$ is the tail index. A low (high) tail index indicates that the tail is fat (thin). The t −statistics and p −value are against the null that $\hat{\alpha}$ −left is equal to $\hat{\alpha}$ −right. The standard deviation of the difference between two tail indices is the bootstrapped difference. The number of block bootstraps equals to 600. The optimal block length is fixed at the total number of observations raised to the power of 1/3, following Hall et al. (1995).

However, higher moment statistics in Table 2.1 demonstrate the potential unattractiveness of momentum strategies, as compared with the market strategy. Momentum returns are very negatively skewed (a skewness of -2.53) and present fat tails (a kurtosis of 21.50). By contrast, returns from the market strategy display a skewness of 0.17 and a kurtosis of 3.24. Separate analysis of the left tail and the right tail show that the momentum return has the thinnest right tail ($\alpha = 3.58$) and the fattest left tail ($\alpha = 1.87$) among all four portfolios in Table 2.1. This attribute of asymmetric tail risk is further confirmed by the expected shortfalls calculated at various confidence levels. As one goes further into the tail from 5% (once in 20 months) to 0.5% (once in 200 months), the expected losses in one month increase from 16.9% to 58.1%, while the expected gains in one month only increases from 12.2% to 23.2%. The sum of right-tail expected shortfall and left-tail expected shortfall remains significantly negative for all tail confidence intervals equal to and better than 5%. These negative sum-of-two-tail (left and right tail) expected shortfalls suggest that the extreme possible losses presented by the momentum strategy are not compensated by a similar size of extreme possible gain.

What is driving the asymmetric tail risks of momentum strategies? The answer also can be found in Table 2.1. The loser's right-tail index is significantly lower than its left-tail index. By contrast, the winners'-tail index estimate shows an opposite effect. The losers have relatively fat right tails and thin left tails and the winners have relatively thin right tails and fat left tails – a momentum investor is exposed to the short losers' fat right tail with no compensating left tail. This effect is corroborated by the tail indices for the momentum portfolio; the left-tail index is lower and the right-tail index is higher than any of the other tail index estimates.

In order to better visualize the asymmetric tail risks of momentum strategy, I further plot left-tail expected shortfalls and right-tail expected shortfalls of the winner portfolio, the loser portfolio, the WML portfolio and the market portfolio, at the 0.5% to 5% confidence level. The plot is shown in Panel A of Figure 2.2. Corresponding plots of the sum-of-two-tails expected shortfalls included in Panel B of Panel 2.2 demonstrate that the momentum strategies have highly asymmetric tail risks. For all confidence levels, the momentum's left-tail expected shortfall significantly exceeds that of the right tail.

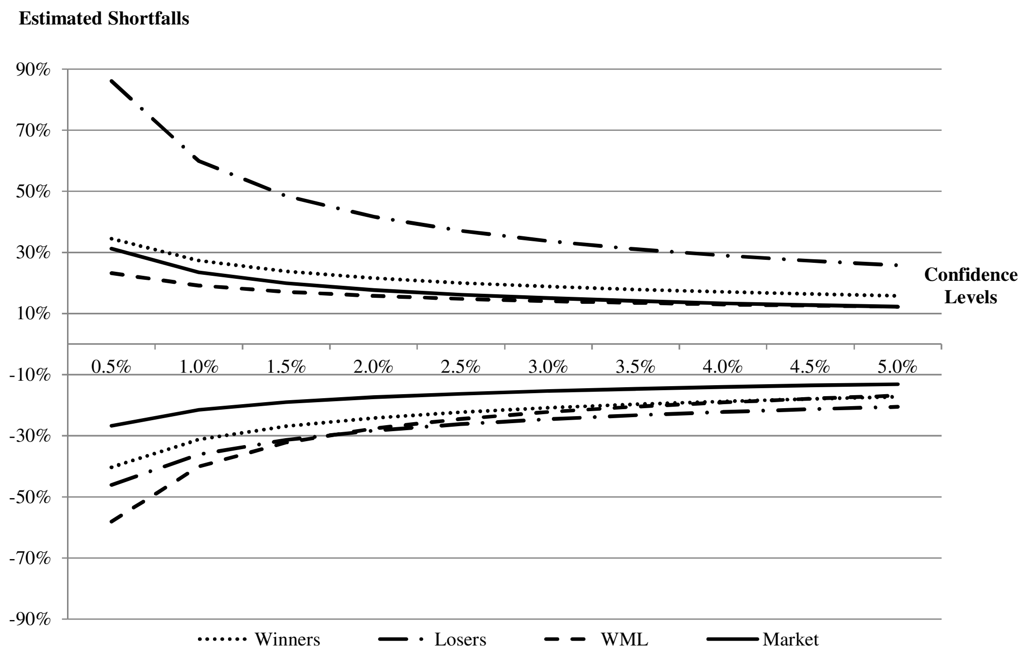
The economic importance of the difference between the left- and right-tail expected shortfall becomes especially pronounced for the most extreme momentum returns. For the 5% confidence level (once every 20 months), the sum of the momentum returns' left- and right-tail expected shortfalls equals -4.73%. For the 0.5% confidence level (once every 200 months), this sum reaches a much greater negative level of -34.92%. By contrast, the expected shortfall estimates of a market strategy are markedly more symmetric: the right-tail expected shortfall levels are quite similar to their left-tail counterparts. As a result, for the market portfolio, the sum-of-two-tails' expected shortfalls hover around zero. Hence, the momentum strategy has, compared with the market strategy, highly undesirable tail return characteristics. A block-bootstrapped t-test shows that the difference between the two portfolios' expected shortfalls is statistically significant for most confidence levels.

Menkhoff and Schmeling (2006) introduce prospect theory to momentum strategy analysis. Taking their work one step further, this essay analyses how prospective utility levels are affected by extreme tail returns. Figure 2.3 demonstrates that the most extreme tail returns are disproportionally important in determining a strategy's total utility. This is most dramatic in evaluation horizons of around a year, and especially when comparing the momentum versus market strategies. This essay introduces the tail utility contribution, which is calculated as the sum of the left and right tails' utility levels, divided by the overall utility. The tail utility contribution thus measures the relative importance of the tails in a portfolio's total utility level. As the evaluation horizon increases, the tail utility contributions strongly increase for the momentum portfolio. In contrast, for the market strategy, the tail utility contributions remain around the same level because its tail risks are more symmetric compared with

Figure 2.2 Asymmetry in expected shortfalls

Plot in Panel B shows the sum of the left and right tails' expected shortfalls for each of four portfolios: winners, losers, momentum (WML) and the market. The confidence level p, from Equation (4), ranges from 0.5% to 5.0%.

A.



B.

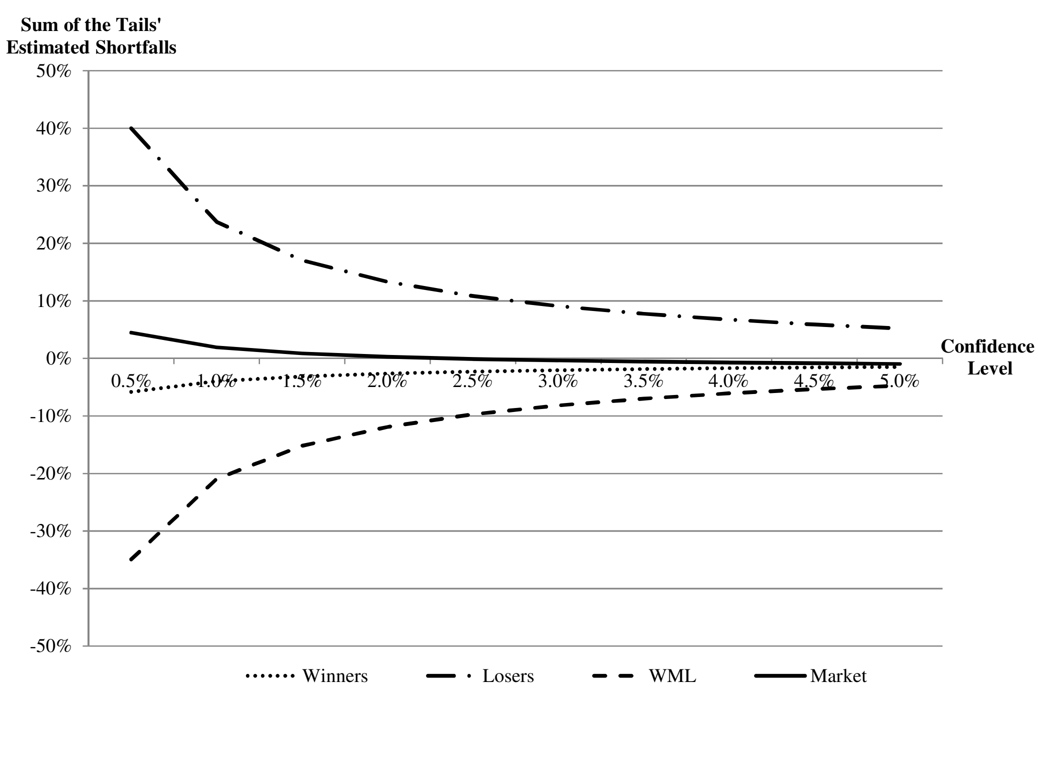
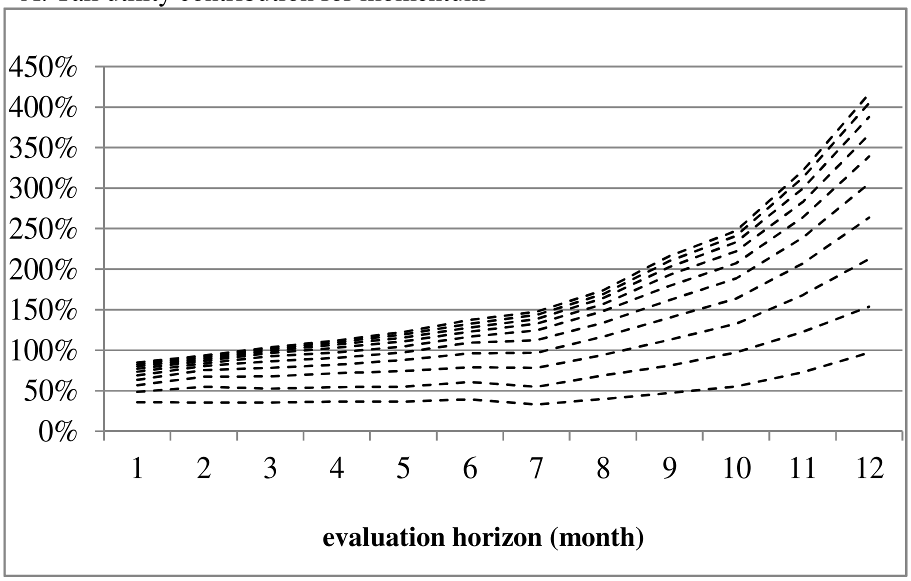


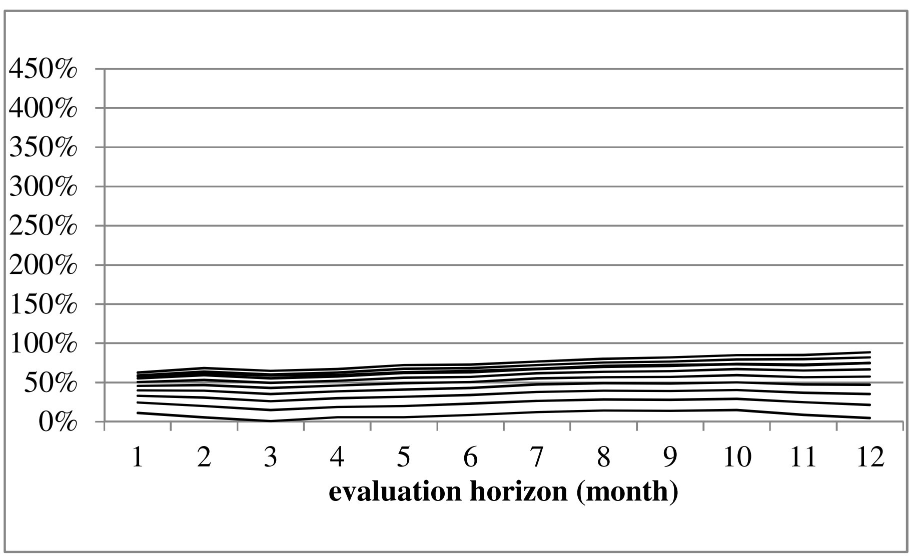
Figure 2.3 Prospective utility tail contributions

This figure reports the contributions of tail observations in determining prospective utility levels for the 6/6 momentum strategy (in Panel (A)) and the market strategy (in Panel (B)) across various evaluation horizons. Based on Menkhoff and Schmeling (2006), I randomly draw 100,000 consecutive n-month returns from the sample, and then rank them to calculate 200 interval means as inputs into the prospective utility function. The tail utility contribution reports the sum of the utility on the left and right tails divided by the total utility. The lines report tail utility contributions for confidence intervals ranging from 0.5% (bottom line in each panel) to 5.0% (highest line in each panel).

A. Tail utility contribution for momentum



B. Tail utility contribution for market portfolio



the momentum portfolio. Finally, Figure 2.3 shows that as one uses more tail observations – that is, as the confidence level p increases from 0.5% to 5.0% – the tail utility contributions increase for both the momentum and the market portfolio. Such increases are more pronounced for the momentum portfolio due to its more asymmetric tail risks.

6. Robustness check

Do the main results still hold if daily returns are examined? How do tail risks estimated at daily frequency compare with tail risks estimated at monthly frequency? Do other momentum strategies also present asymmetric tail risk? Do asymmetric tail risks of momentum returns persist over time? In order to answer these questions, I have repeated the tests in Section 5 on different momentum strategies using monthly data and on the same momentum strategy using daily data. I have obtained results qualitatively similar to those in Section 5.

6.1. Different data frequencies

Table 2.2 presents the summary statistics, tail indices and expected shortfalls of daily momentum returns and market returns.

As one moves from once-in-a-1000-trading-days (or, approximately once in four years) confidence level to once-in-10,000-trading-days (or, approximately once in 40 years) confidence level, a buy-and-hold investor can expect to lose an average of 16.9% in a day and expect to gain an average of 18% in a day. By contrast, a momentum investor would expect much more asymmetric extreme losses and gains – he or she would expect an average once-in-40-years loss of 22.6% but only a 12.8% once-in-40-years daily gain. Thus, daily momentum returns exhibit similar asymmetric extreme tail risks, just like monthly momentum returns.

Table 2.2 Daily momentum return characteristics

This table presents the summary statistics of daily returns from an overlapping 6/6 momentum strategy (identical to that used in Jegadeesh and Titman, 2001) and daily returns from a market strategy for the period starting December 1926 and ending December 2009. The kurtosis presented in this table is excess kurtosis. $\hat{\alpha}$ is the tail index. A low (high) tail index indicates that the tail is fat (thin). The order statistics k is chosen to be 250 for winners, losers and WML and 60 for the market returns, respectively.

	Winners	Losers	WML	Market(excess return)
Minimum	-16.6%	-17.5%	-18.1%	-17.1%
Maximum	24.1%	23.1%	11.9%	15.5%
Mean	0.1%	0.0%	0.0%	0.0%
St. dev.	1.4%	1.5%	0.9%	1.1%
Skew	-0.28	0.62	-1.24	-0.12
Kurtosis	20.64	19.50	24.17	17.49
$\hat{\alpha}$-Left	2.67	3.06	2.76	3.63
$\hat{\alpha}$-Right	2.85	2.70	3.32	2.75
Expected shortfall (Left, 0.1%)	-15.3%	-13.6%	-9.8%	-8.9%
Expected shortfall (Right, 0.1%)	12.7%	16.9%	6.4%	7.8%
Expected shortfall (Left, 0.05%)	-19.9%	-17.0%	-12.6%	-10.8%
Expected shortfall (Right, 0.05%)	16.2%	21.9%	7.9%	10.0%
Expected shortfall (Left, 0.025%)	-25.8%	-21.3%	-16.2%	-13.1%
Expected shortfall (Right, 0.025%)	20.7%	28.2%	9.7%	12.9%
Expected shortfall (Left, 0.01%)	-36.4%	-28.7%	-22.6%	-16.9%
Expected shortfall (Right, 0.01%)	28.5%	39.6%	12.8%	18.0%

6.2. Reconcile results using daily data with results using monthly data

I use equation (5) to calculate 20-day expected shortfalls from one-day expected shortfalls. Table 2.3 presents the comparison of 20-day expected shortfalls estimated from daily data with one-month expected shortfalls estimated from monthly data, for corresponding confidence levels.

Table 2.3 Expected shortfalls comparison: estimates from daily data against estimates from monthly data

This table presents the reconciliation from daily expected shortfalls to monthly expected shortfalls. Daily expected shortfalls are estimated using daily returns of an overlapping 6/6 strategy from 1 December 1926 to 31 December 2009. Monthly expected shortfalls are estimated using monthly returns of the same strategy during the same period. I have used Equation (3) to calculate N-day expected shortfalls. One month contains 20 trading days. One year contains 250 trading days.

Daily p	Once in N Years	Equivalent Monthly p	Tail	20 Trading Days expected shortall (using daily data)	One-month expected shortfall (using monthly data)
0.025%	16	0.05%	Left	-72.6%	-58.1%
			Right	43.4%	23.2%
0.050%	8	1.00%	Left	-56.5%	-40.1%
			Right	35.2%	19.1%
0.10%	4	2.50%	Left	-44.0%	-24.5%
			Right	28.6%	14.8%

In Table 2.3, the 20-day expected shortfalls are systematically larger, in absolute terms, than one-month estimated shortfalls (for example, the once-in-16-years 20-day expected shortfall is -72.6%; while the once-in-16-years one-month expected shortfall is -58.1%). An interesting auxiliary result in this essay is that Equation (5) systematically over-estimates 20-day expected shortfall. These overestimates are surprising at first sight but can be explained by the well-known volatility clustering presented in daily stock returns. The underlying assumption in Equation (5) is that daily returns are i.i.d. However, it is well known that daily stock return data exhibit volatility clustering. That is, large changes in prices tend to cluster together and daily extreme gains and losses tend to cancel each other out to a certain extent in the monthly data. Thus, the monthly expected shortfalls are smaller than the 20-day expected shortfall estimated from Equation (5). This empirical discrepancy suggests that the square root of days rule in Equation (5) is a better approximation for very short periods (perhaps no more than a few days).

6.3. Different momentum strategies

My conclusion remains the same if tail risks are assessed on various momentum strategies. Other momentum strategies studied in this essay include an un-restricted 12/1/1 momentum strategy and a restricted momentum strategy. The un-restricted 12/1/1 strategy is the strategy studied by Menkhoff and Schmeling (2006) and Fama and French (1996), where stocks are ranked based on previous 12-month cumulative returns, skip one month to avoid impact from bid-ask bounce and the top- (bottom-) decile stocks are held (short) for one month. I refer to this strategy as an un-restricted strategy because low-price stocks and small capitalization stocks are not excluded from ranking. Thus, implementation of un-restricted momentum strategies will require buying and shorting these difficult-to-short and illiquid stocks. In order to assess the impact on momentum return distribution from these low-price and small capitalization stocks, I also generate returns from a restricted 12/1/1 strategy, where low-price and small-capitalization stocks are excluded from ranking.

The monthly return distribution of an overlapping 6/6 momentum strategy (the strategy examined in the main results section) is very similar to that of a restricted 12/1/1 strategy. More interesting, when low-price and small-capitalization stocks are included, the non-restricted 12/1/1 momentum returns are dramatically more negatively skewed and fatter tailed than returns from the restricted 12/1/1 strategy. The 12/1/1 unrestricted strategy yields a skewness of -2.98 and a kurtosis of 24.66; the 12/1/1 restricted strategy yields a skewness of -0.20 and a kurtosis of 5.99. This is the second interesting auxiliary result – the inclusion of low-price and small-capitalization stocks dramatically increases the higher-moment risks of moment strategies.

6.4. Rolling-window analysis

In this section, I investigate how a momentum strategy's extreme losses and gains change over time. At the end of each month, expected shortfalls are calculated from the previous 2,000 days' momentum returns; these are the realized expected shortfalls for that month. My results based on a 1000 day rolling window are qualitatively similar.

Figure 2.4 illustrates that the left-tail and right-tail expected shortfalls for market excess returns, the winner portfolio (P1), the loser portfolio (P10) and the winner-minus-loser portfolio (P11) change dramatically over time. More interestingly, the blue lines show that P1 and P11 tend to have a larger left-tail risk than the right-tail upside for a majority of the time periods studies.

Table 2.4 provides more statistical information on the rolling-window expected shortfalls. P11 (WML) has larger downsides than upsides for 98.9% of the total periods, resulting in a -1.3 skewness of tail asymmetry (the left- plus right-tail expected shortfall), the lowest among all portfolios. This can be primarily driven by the tail behaviour of P1 (winner), which has a negative tail asymmetry for 78.1% of the total periods. P10 (loser) has a positive tail asymmetry for 53.5% (1 minus 46.5%) of the total period and positively skewed expected shortfalls – shorting a portfolio with positively skewed tail risks further adds to the downsides of P11. These results are consistent with those from monthly data.

Are momentum tail risks related to business cycles? Table 2.4 reports the tail asymmetry conditional on economic cycles. Expansion periods have a higher portion of negative tail asymmetry than average. At almost all (98.9%) observation points, momentum returns have negative tail asymmetry, where estimated left-tail expected shortfalls exceed that of the right tail. That is, if a momentum investor assesses his or her tail risk on each day, using past 2000 or 1000 daily momentum returns, he or she will in 98.9% of time expect higher extreme losses than extreme gains. Further, this asymmetric tail risk appears to be similar during expansions and recessions, where during expansion (recession) in 99.4% (96.5%) of occasions expected shortfalls on the left tail exceed those on the right tail.

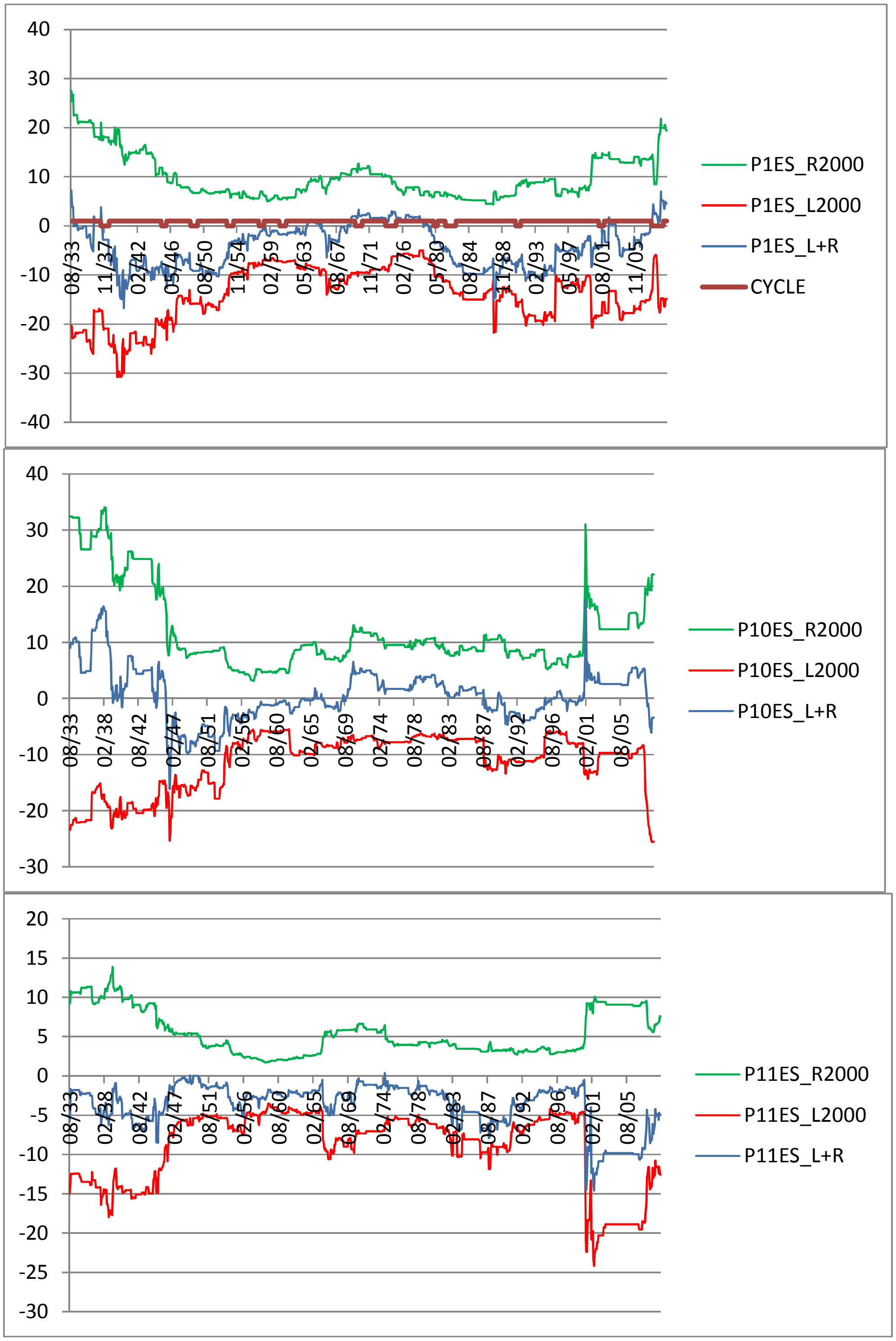
This figure depicts the monthly rolling-window expected shortfalls from an overlapping 6/6 strategy. The sample period is 12/1925–12/2009. Daily momentum returns from 08/1933 to 12/2009 are generated using total returns of all NYSE/AMEX/NASDAQ stocks. Stocks within the lowest NYSE market capitalization decile and with a lower than $5 closing price on the previous trading day are excluded from the ranking period. For the estimate of expected shortfall, p is set at 0.001 (once in 1,000 trading days) and order statistics k at 50. MktrfES_L2000 denotes the left-tail expected shortfalls of market excess returns estimated using the previous 2,000 days' returns. P1 is the winner portfolio. P10 is the loser portfolio. P11 is the WML portfolio.

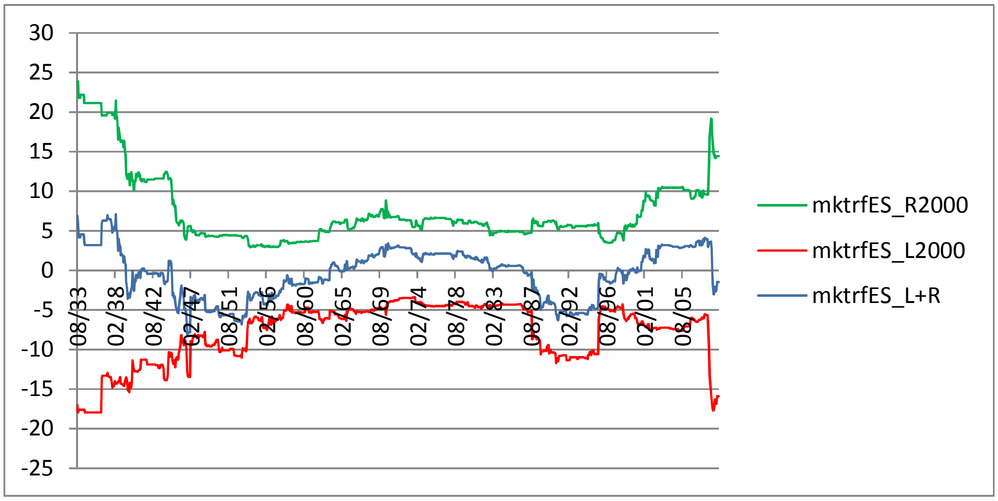
7. Conclusion

Using extreme value theory, this essay finds that the winner stocks and loser stocks in a momentum portfolio exhibit very different tail characteristics, which contribute to both the momentum portfolio's fat left tail and thin right tail. This asymmetry becomes especially evident in the most extreme momentum returns. By contrast, the tail returns of a market portfolio are significantly less asymmetric. This tail asymmetry exists in daily momentum returns, for different momentum strategies, persists over time and is unrelated to business cycles.

The asymmetry of the extreme tail risks strongly reduces a momentum strategy's overall utility levels. This asymmetric tail risk makes a momentum strategy unattractive compared with a buy-and-hold strategy.

Figure 2.4 Rolling-window estimated shortfalls





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02/92
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mktrfES_R2000
mktrfES_L2000
mktrfES_L+R

Table 2.4 Summary statistics of rolling-window expected shortfalls

This table reports the monthly rolling-window expected shortfalls from an overlapping 6/6 strategy from 08/1933 to 12/2009 using total returns of all NYSE/AMEX/NASDAQ stocks. Stocks within the lowest NYSE market capitalization decile and with a most recent closing price lower than $5 are excluded from the ranking period. P=0.001 (once in 1,000 trading days). Order statistics k =50. Tail-asymmetry is defined as the sum of left-tail and right-tail expected shortfalls.

									% of obs with negative tail-asymmetry		
		# of obs	min.	max.	mean	S.D.	skewness	kurtosis	full sample	expansion	contraction
market portfolio	Left-tail ES	917	-18.0	-3.4	-7.9	3.74	-1.01	0.21	n.a.	n.a.	n.a.
	Right-tail ES	917	2.9	23.9	7.5	4.47	1.84	2.87	n.a.	n.a.	n.a.
	Tail-asymmetry	917	-8.1	7.1	-0.4	3.12	-0.25	-0.76	49.8%	51.4%	41.3%
P1 (winners)	Left-tail ES	917	-30.8	-5.0	-14.0	5.5	-0.5	-0.4	n.a.	n.a.	n.a.
	Right-tail ES	917	4.4	27.5	9.9	4.4	1.2	0.9	n.a.	n.a.	n.a.
	Tail-asymmetry	917	-16.8	7.2	-4.1	4.4	-0.1	-1.0	78.1%	80.2%	66.4%
P10 (losers)	Left-tail ES	917	-25.5	-5.5	-11.3	5.0	-1.0	-0.3	n.a.	n.a.	n.a.
	Right-tail ES	917	3.2	34.0	12.0	7.1	1.5	1.2	n.a.	n.a.	n.a.
	Tail-asymmetry	917	-16.1	17.5	0.7	4.6	0.4	1.5	46.5%	48.3%	36.4%
P11 (WML)	Left-tail ES	917	-24.2	-3.5	-9.1	4.8	-1.0	-0.1	n.a.	n.a.	n.a.
	Right-tail ES	917	1.7	13.8	5.4	2.8	0.7	-0.7	n.a.	n.a.	n.a.
	Tail-asymmetry	917	-14.6	0.4	-3.7	2.8	-1.3	1.2	98.9%	99.4%	96.5%

Chapter 3 Predictability in Carry Trades and an Evaluation of Alternative Explanations[1]

Abstract

Predictability in dynamic carry trades is leg-specific. The world equity index return positively predicts short-leg profits, while changes in the commodity index positively predict long-leg profits. Changes in currency volatility and changes in equity volatility negatively predict the profit from both legs of carry trades, but at different monthly lags. Market-timing strategies utilizing these leg-specific prediction models lead to higher carry trade profits (after bid-ask spreads), higher Sharpe ratios and improved skewness. Evidence from this study points towards gradual information diffusion as a likely explanation, while time-varying risk premia do not seem to explain this predictability.

JEL classifications: G11, G14, F31

Keywords: Carry Trade; Return Predictability; Safe-haven Currencies; Volatility; Gradual Information Diffusion; Time-varying Risk Premium

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[1] This chapter is a paper I co-authored with Professor Ben Jacobsen.

1. Introduction

Currency carry trade strategies involve borrowing in a low-yielding *funding* currency and lending in a higher-yielding *investment* (or *target*) currency. Payoffs from these investments depend on both the interest rate differentials and exchange rate movements. Carry trades have become a common strategy employed both by practitioners and retail investors, and are evident in the growing number of available financial products based on the carry (or *the interest rate differential*). This potentially lucrative strategy does, however, present substantial downside risks. For example, carry traders suffered heavy losses during the episodes of strong yen appreciation in 1998 after the LTCM crisis, and when the Australian dollar and New Zealand dollar fell sharply in 2008 during the global financial crisis.

A recent study by Bakshi and Panayotov (2012) has revealed strong predictability in dynamic carry trade profits and shows that U.S. investors would be better off timing the market based on their model predictions than staying fully invested in dynamic carry trades. The dynamic strategies in their paper are monthly rebalancing equal-weighted carry trade strategies (from here onwards, *carry trade* in this paper refers to this strategy). Specifically, at the end of each month, a U.S. investor ranks the G-10 currencies according to their interest rate differentials embedded in forward discounts; then, one-month forward contracts are bought on the highest-yielding currencies (or the *long* leg of carry trades) and one-month forward contracts are sold on the lowest-yielding currencies (or the *short* leg of carry trades). They uncover three predictors for *monthly* dynamic carry trade profits, namely, quarterly changes in a commodity index, quarterly changes in currency volatility and quarterly changes in liquidity.

This study is motivated by two interesting results in Bakshi and Panayotov (2012). First, they show that the predictability in dynamic carry trade profits is from the long leg but not the short leg. Second, the asset pricing tests conducted in their paper provide mixed evidence regarding whether risk premia explain the discovered predictability.[6]

This paper takes their work a step further by uncovering predictability in low-yielding currencies and showing that the discussed predictability in carry trades is more consistent with the hypothesis that information gradually flows across asset markets (or, the *gradual information diffusion* hypothesis, by Hong and Stein, 1999, and Hong, Torous and Valkanov, 2007), rather than a result of time-varying risk premia.

In order to investigate predictability in low-yielding currencies and high-yielding currencies and test the gradual information diffusion hypothesis, I adopt an empirical approach different from that taken by Bakshi and Panayotov (2012) in three respects. *First*, I examine the profits from the short leg and the profits from the long leg of carry trades separately. This leg-specific investigation is motivated by the fact that low-yielding currencies and high-yielding currencies do *not* tend to move together, and thus they may be driven by different economic factors. *Second*, in addition to predictors tested in their paper, I include the MSCI World Price Index return as a new predictor, motivated by the finding that low-yielding currencies tend to depreciate when equity prices rise (for example, Ranaldo and Söderlind, 2010; Campbell, Medeiros and Viceira, 2010). *Third*, instead of using quarterly changes in independent variables to predict changes in carry trade profits in the following month, I investigate whether carry trade profits in month t are predictable from related economic variables in each of month $t-1$, month $t-2$ and month $t-3$. This study chooses three monthly lags of predictors in order to investigate whether the predictability is consistent with the gradual information hypothesis by Hong and Stein (1999) and Hong, Torous and Valkanov (2007), which models short-run cross-asset predictability as a result of gradual information flow across financial markets. The model

[6] In Bakshi and Panayotov (2012), the latent-variable model tests support the time-varying risk explanation, but the test developed by Kirby (1998) rejects the time-varying risk explanation.

specifications in this paper closely resemble those in Hong, Torous and Valkanov (2007, Table 3.3).

Using dynamic carry trade profits (after crossing bid-ask spreads) constructed for G-10 currencies from January 1985 to December 2011, I find leg-specific predictability in carry trade profits. *First*, monthly world equity index return positively predicts monthly short-leg profits but not the long-leg profits, while monthly changes in the commodity index positively predict monthly long-leg profits but not the short-leg profits. Drops in the world equity index in one month tend to be followed by drops in the short-leg profit two months later. Monthly commodity price changes positively predict the long-leg profit after three months. *Second*, changes in currency volatility and changes in equity volatility negatively predict the profit from both legs of carry trades, but the predictive effect shows up at different monthly lags. If equity market volatility increases in this month, the short-leg profit tends to drop in two months' time. Similarly, currency market volatility changes also negatively predict the short-leg profit after two months. In contrast, changes in equity volatility and changes in currency volatility tend to negatively affect high-yielding currencies three months later.

The choice of predictors is motivated by recent studies on currency portfolio returns. The world equity index return is employed as a predictor for profits from the short leg, because low-yielding currencies (or *safe-haven currencies*) tend to depreciate when equity prices rise (for example, Ranaldo and Söderlind, 2010; Campbell, Medeiros and Viceira, 2010). Studies on commodity currencies (Chen, Rogoff and Rossi, 2010) motivate the choice of commodity price changes as a predictor for the long-leg carry trade profit. Based on evidence for the contemporaneous relation between equity volatility changes and currency returns (Lustig, Roussanov and Verdelhan, 2011) and the contemporaneous relation between currency volatility changes and currency returns (Menkhoff, Sarno Schmeling and Schrimp, 2012), this study tests whether changes in equity volatility and changes in currency volatility also predict each leg of dynamic carry trades.

The size of predictive coefficients is also economically significant. For example, a one standard deviation shock in the world equity index level can lead to an annualized decrease of 5.35% (about 0.6 standard deviations) in short-leg profits. A one standard deviation increase in the equity volatility and a one standard deviation increase in the currency volatility can each lead to an annualized decrease of approximately 0.9 and 0.5 standard deviations, respectively, in profits from the short-leg carry trade. For the long leg of carry trades, a one standard deviation shock in commodity prices can forecast an annualized decrease of 7.16% (about 0.7 standard deviations) in profits. A one standard deviation increase in the equity volatility and a one standard deviation increase in the currency volatility can each lead to annualized decreases of approximately 0.5 and 0.4 standard deviations, respectively, in profits from the long-leg carry trade.

One might suspect that the discovered predictability is driven by the recent financial crisis. I plot predictive coefficients from rolling-window regressions over time. While all predictive coefficients vary over time, they do not exhibit clear trends or sudden changes around the recent financial crisis.

Out-of-sample results confirm the in-sample findings and rolling-window results. The observed in-sample predictability in carry trade profits could have helped investors. Using the out-of-sample R^2 statistic, as in Goyal and Welch (2008), and the MSPE-adjusted one-sided p-values, developed by Clark and West (2007), I find that these predictors consistently deliver better prediction than the benchmark model.

The leg-specific predictability has economic value for carry trade investors. If carry traders decide whether to establish positions on the short leg and on the long leg separately using leg-specific prediction models, they can improve profits, Sharpe ratios and skewness profile, relative to outcomes from always investing in carry trades, and relative to outcomes from predicting long/short profits with a single model. The improvement in trading profits in this study is achievable in a real trading environment because I consistently incorporate bid-ask spreads.

The in-sample result is robust to other predictors found to be important to carry trades and currency returns, in particular, changes in global liquidity (as per

Brunnermeier, Nagel and Pedersen, 2008), the term premium (as in Ang and Chen, 2010) and average forward discount and percentage change in the industrial production of the OECD countries (as documented in Lustig, Roussanov, Verdelhan and Sloan, 2012). Changes in the CBOE VIX index (based on Brunnermeier, Nagel and Pedersen, 2008) also have some success in predicting carry trade profits, but only for the short-leg, while its predictive ability becomes insignificant in the presence of the world equity index return.

Equity prices, commodity prices, realized equity volatility and realized currency volatility are all publicly available information. One can easily obtain this information on a real-time basis. It is surprising that investors can use these variables to forecast carry trade profits, time the market and improve their profits. If, however, we are willing to assume that investors all have limited processing capacity (or are *bounded rational*, Sims, 2003) and that interpreting changes in these predictors is not always straightforward, then information can gradually flow across investors and markets, generating return predictability. Since Hong and Stein (1999) first introduced this gradual information diffusion hypothesis, a large number of studies have uncovered short-run return predictability that is consistent with predictions from this model (for example, Hong, Kubik and Solomon, 2000; Hong, Lim and Stein, 2000; Hong, Torous and Valkanov, 2007; Driesprong, Jacobsen and Maat, 2008; Menzly and Ozbas, 2010; Rizova, 2011; Rapach, Strauss and Zhou, 2012). Evidence in this paper, based on the results from two tests, is consistent with the gradual information diffusion hypothesis. *First*, this essay follows Driesprong, Jacobsen and Maat (2008) and introduces different sizes of lags between carry trade profits and predictors, in order to examine how the explanatory power of predictive regressions changes as the lag size increases. As the lag lengthens, the predictability in both low- and high-yielding currencies initially peaks, and then quickly drops. This pattern is more consistent with a gradual information diffusion explanation. *Second*, I recognize that the gradual information diffusion hypothesis might not be the only explanation for the findings in this paper. Similar to stock returns, carry trade profits also vary across business cycles (as shown by Lustig, Roussanov, Verdelhan and Sloan, 2012). Thus, a testable prediction of the gradual information diffusion model by Hong, Torous and Valkanov (2007, p.372) is that variables that strongly predict carry trade profits should also forecast market fundamentals such as industrial production growth. Following their approach, this essay shows that the ability of a variable to predict either short-leg carry trade profits or long-leg carry trade profits strongly correlates with its propensity to forecast industrial growth in OECD countries. The same variables that positively (negatively) predict carry trade profits also positively (negatively) predict industrial production growth. For example, rises in the world equity index means good news for future economic activity and for carry trades, while increased equity volatility and increase currency volatility mean just the opposite.

This paper contributes to the literature in three respects. First, this study documents statistically and economically significant predictability in the low-yielding currencies. This short-run predictability in low-yielding currencies is new and interesting in itself. Second, this study demonstrates the economic relevance of using different models to predict low- and high-yielding currencies. If an investor conditions his or her carry trade decision on predicted profits for each leg of carry trade, he or she could have achieved trading outcomes with a higher mean, higher Sharpe ratios and improved skewness, than by simply going ahead with carry trades every month. Finally, existing studies have uncovered substantial evidence for cross-market and cross-asset return predictability consistent with the gradual information diffusion hypothesis put forward by Hong and Stein (1999) and Hong, Torous and Valkanov (2007). This study contributes to this strand of literature by showing that the predictability in short-run dynamic carry trade profits is more consistent with the gradual information diffusion hypothesis, instead of a time-varying risk-premia explanation. Unlike predictability from the time-varying risk premia, the predictive effect is short-lived. More importantly, in equilibrium, expected carry trade profits should increase in the face of higher uncertainty (lower stock prices, lower commodity prices, higher currency volatility and equity volatility). The effect found in this study is, however, precisely the opposite: lower stock prices (lower commodity prices and higher volatility) reduce future carry trade profits. Schwert (2003) suggests a standard to distinguish between return predictability due to market inefficiency and return predictability from time-varying risk premia. He states that when predictability is not the result of time-varying equilibrium returns, the excess stock returns should be predictably negative. The world equity index return and commodity price movements appear to meet this standard, because they frequently predict many negative carry trade profits.

2. Dynamic carry trade strategies

This study consistently incorporates bid-ask spreads in computing profits from dynamic carry trade strategies. That is, all carry trade profits in this study are achievable in a real-life environment. This section introduces the construction of dynamic carry trade profits and some interesting attributes of these profits.

2.1. Construction of dynamic carry trade strategies

This chapter studies the predictability in dynamic carry trade profits, after transaction costs, from the perspective of a U.S. investor. That is, I implement carry trades using forward contracts after crossing the bid-ask spread and express profits in U.S. dollar terms, as in Lustig, Roussanov and Verdelhan (2011), Burnside, Eichenbaum, Kleshchelski and Rebelo (2011) and Bakshi and Panayotov (2012). Exchange rates are quoted as U.S. dollars per foreign currency unit (FCU). Therefore, a U.S. investor sells a foreign currency forward at the bid price if it is at a forward premium and buys a foreign currency forward at the ask price if it is at a forward discount.[7]

This essay uses spot and forward exchange rates provided by Barclays Capital via Datastream for G-10 currencies from January 1985 to December 2011.[8] Many investable carry trade indices use G-10 currencies as the universe of their constituent

[7] The ask (bid) exchange rate is the rate at which a participant in the interdealer market can buy (sell) foreign currency from (to) a currency dealer.

[8] Forward rate data for the Australian dollar, New Zealand dollar, Norwegian krone and Swedish krona are unavailable before January 1985.

currencies.[9] G-10 currencies are also the 10 most actively traded free float currencies in terms of daily average turnover. According to the triennial survey conducted by the Bank for International Settlements (BIS) in April 2010, the G-10 currencies accounted for 88% of global foreign exchange market average daily turnover in April 2010. The G-10 currencies include the Australian dollar (AUD), the Canadian dollar (CAD), the Swiss franc (CHF), the euro (EUR), the British pound (GBP), the Japanese yen (JPY), the Norwegian krone (NOK), the New Zealand dollar (NZD), the Swedish krona (SEK) and the U.S. dollar (USD). Similar to Ranaldo and Söderlind (2010), I connect the Deutsche mark (DEM) series (1985–1998) with the euro series (1999–2011) as a single time series for the euro.

The dynamic equal-weighted carry trade strategies studied in this paper are based on a simple rule utilized by many carry trade indices. Specifically, at the end of each month, an investor ranks currencies based on their realizable interest rate differentials inferred from spot and forward rates, and then takes equal-weighted short and long positions in one to three currencies for one month, without leverage. Specifically, I rank currencies based on realizable interest rate differentials inferred from corresponding bid and ask quotes, in order to imitate real-life investment decisions.[10]

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[9] For example, constituent currencies for the iPath Optimized Currency Carry ETN and the Powershares DB G10 Currency Harvest Fund are G-10 currencies.

[10] For example, based on mid-quotes, the Canadian dollar was at a narrow forward premium against the U.S. dollar for many months and, hence, should have been sold forward. These forward premia were, however, so narrow that the potential profit from selling the Canadian dollar forward would often be negative after crossing the bid-ask spreads. In these situations, the Canadian dollar is not, in practice, an attractive funding currency for a U.S. investor. Also, less liquid high-yielding currencies can appear to be more attractive than they are in practice if bid-ask spreads are ignored. For example, based on mid-quotes, the Norwegian krone spent more months as one of the three highest-yielding currencies than the British pound. Once bid-ask spreads are accounted for, the British pound has spent more months than the Norwegian krone as one of the three highest-yielding currencies.

Realizable interest rate differentials against the USD are inferred from the forward rate at the end of month t for delivery at the end of month $t+1$ (F_t) and the spot rate at the end of month t (S_t) after crossing the bid-ask spreads using Equation (1) :

$$idiff_t = \begin{cases} \frac{S_t^{ask}}{F_t^{bid}} - 1 & if\ F_t^{bid} > S_t^{ask} \\ \frac{S_t^{bid}}{F_t^{ask}} - 1 & if\ F_t^{ask} < S_t^{bid} \\ 0 & otherwise \end{cases} \quad (1)$$

Then, I rank currencies according to their realizable interest rate differentials in each month. The U.S. dollar, the Japanese yen and the Swiss franc have been among the three lowest-yielding currencies about two-thirds of the time (out of 324 months). In contrast, the New Zealand dollar, the Australian dollar and the British pound were almost never funding currencies; instead, they spent more than half to two-thirds of the time among the three highest-yielding currencies (Appendix 3.A.).

All profits are scaled to a bet size of one U.S. dollar. Strategy K ($K = 1 \cdots 3$) on short leg (long leg) involves selling (buying) forward one U.S. dollar equivalent of K lowest-yielding (highest-yielding) currencies against the U.S. dollar. In the long/short strategy K, half of the U.S. dollar is best on each leg to maintain a total bet size of one U.S. dollar. Only currencies with negative (positive) realizable interest rate differentials against the U.S. dollar can be sold (bought) forward. When the U.S. dollar is the lowest-yielding currency in any month, the weights are adjusted accordingly in order to maintain a total bet size of one U.S. dollar. This equal-weighted strategy is re-balanced monthly, based on realizable interest rate differentials.

The profit from this dynamic strategy is specified in Equation (2):

$$P_{t+1}^{j_{short}} = \frac{1}{F_t^{bid(j^{th}\ lowest)}}\left(F_t^{bid(j^{th}\ lowest)} - S_{t+1}^{ask(j^{th}\ lowest)}\right),$$

$$P_{t+1}^{j_{long}} = -\frac{1}{F_t^{ask(j^{th}\ highest)}}\left(F_t^{ask(j^{th}\ highest)} - S_{t+1}^{bid(j^{th}\ highest)}\right), \quad j = 1 \cdots 3$$

$\overline{P}_{t+1}^{K_{short}} = \frac{1}{K}\sum_{j=1}^{K} P_{t+1}^{j_{short}}, \quad \overline{P}_{t+1}^{K_{long}} = \frac{1}{K}\sum_{j=1}^{K} P_{t+1}^{j_{long}}$, and

$$\overline{P}_{t+1}^{K_{long/short}} = \begin{cases} \frac{\overline{P}_{t+1}^{K_{short}} + \overline{P}_{t+1}^{K_{long}}}{2} & , when\ USD\ is\ not\ the\ lowest-yielding\ currency \\ \overline{P}_{t+1}^{K_{long}} & ,\ when\ USD\ is\ the\ lowest-yielding\ currency \end{cases}$$

$$, k = 1 \cdots 3 \text{ , (2)}$$

where $P_{t+1}^{j_{short}}$ ($P_{t+1}^{j_{long}}$) is the profit over month $t+1$ from selling (buying) the jth lowest-yielding (highest-yielding) currencies; $\overline{P}_{t+1}^{K_{short}}$ ($\overline{P}_{t+1}^{K_{long}}$) is the profit over month $t+1$ from taking K short (long) positions in a total of K lowest-yielding (highest-yielding) currencies, or the short-leg (long-leg) profit; and $\overline{P}_{t+1}^{K_{long/short}}$ is the long/short strategy profit (long/short profits), from simultaneously taking K long/short positions in the highest- and lowest-yielding currencies in month $t+1$.

2.2. Profits from dynamic carry trades

How profitable are dynamic carry trades and, particularly, how much does each leg of carry trades contribute to overall profitability? Have exchange rate movements increased, or decreased, carry trade profits for each leg? Table 3.1 contains such basic information on profits from each leg and the long/short strategy.

Table 3.1 Carry trade profits

This table reports the summary statistics of carry trade profits from three dynamic strategies from January 1985 to December 2011. All profits are denominated in USD and from a bet size of one dollar.

I consider three dynamic carry trade strategies (K=1⋯3). In strategy K, a total of K currencies are bought or sold forward against the U.S. dollar. The profit from this dynamic strategy is constructed as (following Bakshi and Panayotov, 2012):

$$P_{t+1}^{j_{short}} = \frac{1}{F_t^{bid(j^{th}\ lowest)}}\left(F_t^{bid(j^{th}\ lowest)} - S_{t+1}^{ask(j^{th}\ lowest)}\right),$$

$$P_{t+1}^{j_{long}} = -\frac{1}{F_t^{ask(j^{th}\ highest)}}\left(F_t^{ask(j^{th}\ highest)} - S_{t+1}^{bid(j^{th}\ highest)}\right), \quad j = 1 \cdots 3$$

$$\overline{P}_{t+1}^{K_{short}} = \frac{1}{K}\sum_{j=1}^{K} P_{t+1}^{j_{short}}, \quad \overline{P}_{t+1}^{K_{long}} = \frac{1}{K}\sum_{j=1}^{K} P_{t+1}^{j_{long}}, \text{ and}$$

$$\overline{P}_{t+1}^{K_{long/short}} = \begin{cases} \dfrac{\overline{P}_{t+1}^{K_{short}} + \overline{P}_{t+1}^{K_{long}}}{2}, when\ USD\ is\ not\ the\ lowest-yielding\ currency \\ \overline{P}_{t+1}^{K_{long}},\ when\ USD\ is\ the\ lowest-yielding\ currency \end{cases}, k = 1 \cdots 3,$$

where S_{t+1} denotes the spot exchange rate expressed as USD per FCU at the end of month $t+1$, F_t is the corresponding monthly forward rate known at the end of t , for delivery at the end of month t+1. $P_{t+1}^{j_{short}}$ ($P_{t+1}^{j_{long}}$) is the profit over month $t+1$ from selling (buying) the j lowest-yielding (highest-yielding) currencies; $\bar{P}_{t+1}^{K_{short}}$ ($\bar{P}_{t+1}^{K_{long}}$) is the profit over month $t+1$ from betting one U.S. dollar on K short (long) positions in the lowest-yielding (highest-yielding) currencies; and, $\overline{P}_{t+1}^{K_{long/short}}$ is the profit from betting half a U.S. dollar on K long positions in the highest-yielding currencies and half a U.S. dollar on K short positions in the lowest yielding currencies in month $t+1$. When the U.S. dollar is the lowest-yielding currency in any month, no currency is shorted against it; in these months, weights are adjusted accordingly to maintain a total bet size of one U.S. dollar.

The interest rate component of carry trade profits is calculated based on Equation (2), with spot rate S_{t+1} replaced by S_t . The currency component of carry trade profit is calculated based on Equation (2), with forward rate F_t replaced by S_t .

rho(-1) denotes the first order autocorrelation coefficient.

	Carry trade profits					Interest component		Currency component	
	Mean	S.D. annual	Sharpe ratio	Skewness monthly	rho(-1)	mean annual	rho(-1) monthly	mean annual	rho(-1) monthly
Panel A. Three dynamic strategies (strategy K uses K currencies on each leg)									
long/short									
K=1	5.48	10.19	0.54	-0.97	0.11	4.07	0.53	1.42	0.12
K=2	4.39	8.48	0.52	-0.39	0.08	3.17	0.65	1.22	0.09
K=3	3.15	7.79	0.40	-0.38	0.10	2.71	0.66	0.44	0.11
short leg									
K=1	-1.00	10.93	-0.09	-0.95	-0.01	2.49	0.60	-3.49	-0.01
K=2	-0.46	9.41	-0.05	-0.46	0.01	1.97	0.66	-2.42	0.01
K=3	-0.67	9.17	-0.07	-0.41	0.01	1.68	0.66	-2.36	0.01
long leg									
K=1	9.31	12.56	0.74	-0.56	0.10	4.24	0.56	5.07	0.08
K=2	7.17	10.99	0.65	-0.36	0.09	3.43	0.70	3.74	0.08
K=3	5.36	9.98	0.54	-0.46	0.10	2.92	0.67	2.44	0.09

Panel B. Correlations between profits from the short-leg, long-leg and long/short strategy (strategy 3)

	short	long	Long/short
short leg	1	-0.36	0.36
long leg		1	0.69
Long/short			1

Dynamic carry trade strategies are profitable on average with annualized average long/short profits between 3.15% and 5.48%. In addition, the positive profits from long/short dynamic carry trade strategies are from investing in high-yielding currencies. An investor would have made positive gains of from 5.36% to 9.31% annually if using the U.S. dollar to purchase high-yielding currencies forward only. In contrast, an investor shorting low-yielding currencies would have made average losses of between -1.00% and -0.46%.

Although profits from all dynamic carry trades are negatively skewed, ranging from -0.97 to -0.36, the skewness profile improves as more currencies are included in a dynamic strategy.

How much do exchange rate movements and interest rate differentials contribute to carry trade profits? Long/short strategies on average produce profits of 2.71% to 4.07% annually from interest differentials, but only 0.44% to 1.42% from currency movements. Interest components are universally positive by construction, but not the currency components. The long-leg of carry trades has experienced desirable currency movements on average, ranging from 2.44% to 5.07% annually and comparable to the interest components. In contrast, appreciations of low-yielding currencies have resulted in negative currency components ranging between -2.36% and -3.49% annually, which make short-leg strategies unprofitable.

Variations in carry trade profits are primarily driven by exchange rate movements because time series autocorrelations in carry trade profits are almost identical to those in their currency components, with first-order autocorrelation varying between -0.01 and 0.12. Interest components of all carry trades are highly persistent, with highly significantly positive first-order autocorrelation ranging from 0.53 to 0.70.

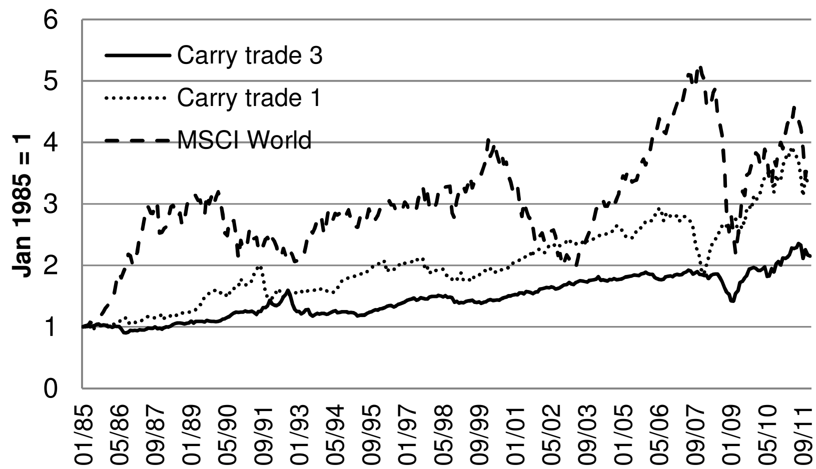
The negative correlation between the long- and short-leg profits (-0.36) suggests that profits from each leg do not tend to move together, or move in the same direction. Closer investigation of the predictability in each leg of carry trades is warranted. At the same time, long/short dynamic carry trade profits are more correlated with profits from the long legs (0.69) than with profits from the short legs (0.36). This high correlation between the long/short profits and long-leg profits raises other questions. How important it is to predict the short-leg profits separately? Could an investor have delivered better prediction by predicting the profits from each leg separately than by simply predicting the long/short profits? I address these issues in Section 6 on economic significance.

Would an investor be better off pursuing carry trades than investing in stock markets? Accumulated profits from both carry trades and from a zero-cost buy-and-hold strategy on the MSCI World Equity Price Index are compared in Figure 3.1. Accumulated profits from carry trade strategies using one currency on each leg and using three currencies on each leg (strategy 1 and 3) would have been \$3.30 and \$2.20, respectively, which is lower than the profit of approximately \$3.70 from simply buying and holding the world equity index. These dynamic carry trade strategies generate profits that are, however, less volatile than those from equity investment. As a result, dynamic carry trade strategies generate more attractive Sharpe ratios, ranging between 0.40 and 0.54, than the 0.35 from buying and holding the MSCI World Equity Price Index.

Long/short carry trade profits and long-leg profits series are slightly positively autocorrelated, with first-order autocorrelations significant in three out of nine profits. The autocorrelation tends, however, to be small, ranging between 0.08 and 0.12. In addition, I explicitly control for autocorrelation in the dependent variables in the remainder of this paper, and Breusch–Godfrey LM tests show no evidence for autocorrelation in the disturbance from regressions specified in Equation (3). Hence, all results in the remainder of this paper are based on White standard errors.

Figure 3.1 Cumulative returns of investment strategies (1985–2011)

The figure plots the cumulative returns for a U.S. investor who begins with $1 in January 1985 and invests his or her returns exclusively in either dynamic carry trade strategy 1 and 3 (one and three currencies on each leg), or the MSCI World Total Return Index (financed at the T-bill rate). Details of the strategies are provided in the text. As the long/short carry trade strategy is a zero-investment strategy, it is compared with cumulative excess returns from borrowing at risk-free rates and investing in the world equity index portfolio. The spot rates, forward rates and MSCI World Total Return Index data are provided by Datastream. The T-bill rate data are from Global Financial Data. The sample period is from January 1985 to December 2011.



3. Predicting carry trade profits from the short leg and the long leg

3.1. Predictors for carry trade profits

Are short- and long-leg carry trade profits driven by common, or different, economic factors? In order to answer these questions, I consider different sets of predictors for short- and long-leg carry trade profits.

Each set of predictors contains two common predictors and one leg-specific predictor. The two common predictors are changes in average equity volatility and changes in average currency volatility. The leg-specific predictors are monthly percentage changes in the MSCI World Equity Price Index for the short-leg profits and monthly percentage changes in the Raw Industrials Spot Commodity Index for the long-leg profits.

Monthly changes in average equity volatility (denoted as $\Delta\sigma_t^{equity}$) and monthly changes in average currency volatility (denoted as $\Delta\sigma_t^{FX}$) are identified by Lustig, Roussanov and Verdelhan (2011) and Menkhoff, Sarno, Schmeling and Schrimpf (2012) as risk factors for explaining currency returns and average carry trade profits, respectively. $\Delta\sigma_t^{equity}$ may serve as a proxy for uncertainty in global equity markets. A country's equity volatility in month t is computed as the standard deviation of daily stock market index returns, with the average equity return volatility being the cross-sectional mean of the country volatility series in this paper. $\Delta\sigma_t^{equity}$ is the difference between the average equity volatility in month t and in month $t-1$. $\Delta\sigma_t^{FX}$ is intended to serve as a proxy for uncertainty in global currency markets. For each G-10 currency included in this study, I calculate monthly volatility as the standard deviation of daily exchange rate percentage changes against the U.S. dollar over a month. The monthly currency volatility averaged across G-10 currencies is the average currency volatility. $\Delta\sigma_t^{FX}$ is the difference between average currency volatility in month t and month $t-1$.

In order to forecast the short-leg profits, this study adopts monthly percentage changes in the MSCI World Equity Price Index, denoted as r_t^{world}, as a predictor.

This choice is motivated by the fact that low-yielding currencies, including the Japanese yen, the Swiss franc, the U.S. dollar and to a certain extent the euro (and the Deutsche mark prior to the euro), are typically considered *safe-haven* currencies. Ranaldo and Söderlind (2010) and Campbell, Medeiros and Viceira (2010) both document that these low-interest currencies appreciate against the U.S. dollar when U.S. stock prices decrease. This study considers the MSCI World Price Index return to be the global counterpart of the S&P 500 return.

For profits from the long leg of carry trade, I also rely on monthly percentage changes in the Raw Industrials Spot Commodity Index[11], denoted as r_t^{CRB}, as a predictor, following Bakshi and Panayotov (2012).

Predictors for the long-leg profit and long/short profit are identical ($\Delta\sigma_t^{equity}$, $\Delta\sigma_t^{FX}$ and r_t^{CRB}), because the long/short dynamic carry trade profit is mostly driven by the long-leg profit (Panel B of Table 3.1).

Appendix 3.B reports the basic characteristics of all predictors considered by this study in, as well as pairwise correlations between the predictors and carry trade profits. The pairwise correlations suggest that the chosen predictors serve as proxies for different economic forces that are not highly correlated, with correlation coefficients ranging between -0.40 (between r_t^{world} and $\Delta\sigma_t^{equity}$) and 0.46 (between $\Delta\sigma_t^{FX}$ and $\Delta\sigma_t^{equity}$). Predictors investigated in this paper are not persistent, with statistically significant, but insubstantial, first-order autocorrelations. Changes in equity volatility and changes in currency volatility tend to reverse in the following month and have a significant first-order autocorrelation of -0.24 and -0.12, respectively. The MSCI World Equity Price Index return and commodity price changes series have statistically significant autocorrelations of 0.11 and 0.34, respectively.

[11] CRB Raw Industrial Spot Index data series are sourced from Datastream.

Performance of other predictors identified by the existing literature for currency returns and carry trade returns has been examined as well. The results are discussed in Section 6.

3.2. In-sample evidence on predictability in carry trade profits

The main regression in this paper differs from Bakshi and Panayotov (2012) in that this paper investigates exactly in which month the predictive effect shows up in the next quarter, for each leg of carry trades. In contrast, their model relies on quarterly changes in predictors to forecast monthly long/short carry trade profits. The model specification below is intended to test whether the predictability is consistent with the gradual information diffusion hypothesis of Hong and Stein (1999) and Hong, Torous and Valkanov (2007). Gradual information diffusion is one type of market inefficiency and manifests itself as short-run return predictability, as shown by Hong, Torous and Valkanov (2007), Rapach, Strauss and Zhou (2012) and Driesprong, Jacobsen and Maat (2008). Following Hong, Torous and Valkanov (2007, Table 3), the in-sample predictive regression is specified in Equation (3):

$$\overline{P}_t^{K_l} = \alpha_i \ + \beta_{Z,i}^{K_l} Z_{t-i} + \gamma_{Z,i}^{K_l} \overline{P}_{t-1}^{K_l} + \mu_t^{K_l}$$

$$(K = 1 \cdots 3, l = short, long, long/short, i = 1 \cdots 3) \ , \qquad (3)$$

where $\overline{P}_t^{K_l}$ denotes the profits either from betting one U.S. dollar on K low-yielding currencies ($\overline{P}_t^{K_{short}}$), or from betting one U.S. dollar on K high-yielding currencies ($\overline{P}_t^{K_{long}}$), or from betting half a U.S. dollar on each leg ($\overline{P}_t^{K_{long/short}}$) and Z_{t-i} denotes a predicting variable. Following Hong, Torous and Valkanov (2007), this paper tests if Z_{t-1} , Z_{t-2} or Z_{t-3} can predict carry trade profits in month t. The individual predictors for the short-leg carry trade profits are $\Delta\sigma_{t-i}^{equity}$, $\Delta\sigma_{t-i}^{FX}$ and r_{t-i}^{world}, and the individual predictors for the long-leg carry trade profits and long/short carry trade profits are r_{t-i}^{CRB}, $\Delta\sigma_{t-i}^{equity}$ and $\Delta\sigma_{t-i}^{FX}$. That is, the predictive ability of each of the three predictors, lagged by one, two and three months, for all nine carry trade profits, are tested. The coefficient estimates of interests are the 81 $\beta_{Z,i}^{K_l}{}'s$. Estimates of predictive coefficients for the short-leg profits ($\beta_{Z,i}^{K_{short}}{'s}$) are reported in Table A of Table 3.2. Estimates of predictive coefficients for the long-leg profits ($\beta_{Z,i}^{K_{long}}{'s}$) and those for the long/short profits ($\beta_{Z,i}^{K_{long/short}}{'s}$) are reported in Panel B and Panel C of Table 3.2, respectively.

Table 3.2 Predicting carry trade profits in-sample with single predictors

This table reports the coefficient estimates for $\boldsymbol{\beta_{Z,i}^{K_l}{'s}}$ from regressions specified in Equation (3):

$$\overline{P}_t^{K_l} = \alpha_i + \beta_{Z,i}^{K_l} Z_{t-i} + \gamma_{Z,i}^{K_l} \overline{P}_{t-1}^{K_l} + \mu_t^{K_l} \quad (K = 1 \cdots 3, l = short, long, long/short, i = 1 \cdots 3)\,, \qquad (3)$$

where $\overline{P}_t^{K_l}$ denotes the profits from betting one U.S. dollar on K low-yielding currencies ($\overline{P}_t^{K_{short}}$), the profits from betting one U.S. dollar on K high-yielding currencies ($\overline{P}_t^{K_{long}}$), and the profits from betting half a U.S. dollar on each leg ($\overline{P}_t^{K_{long/short}}$) and Z_{t-i} is a predicting variable. Following Hong, Torous and Valkanov (2007, Table 3), this paper tests if Z_{t-1} , Z_{t-2}or Z_{t-3} can predict carry trade profits in month t. The individual predictors for the short-leg carry trade profits are the MSCI World Equity Price Index return (r_{t-i}^{world}), changes in equity volatility ($\Delta\sigma_{t-i}^{equity}$) and changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$). The individual predictors for the long-leg carry trade profits and long/short carry trade profits are percentage changes in commodity prices (r_{t-i}^{CRB}), changes in equity volatility ($\Delta\sigma_{t-i}^{equity}$) and changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$). That is, the predictive ability of each of the three predictors, lagged by one, two and three months, for all nine carry trade profits, are tested. The coefficient estimates of interests are the 81 $\beta_{Z,i}^{K_l}{'s}$. Estimates of predictive coefficients for the short-leg profits ($\beta_{Z,i}^{K_{short}}{'s}$) are reported in Panel A. Estimates of predictive coefficients for the long-leg profits ($\beta_{Z,i}^{K_{long}}{'s}$) and those for the long/short profits ($\beta_{Z,i}^{K_{long/short}}{'s}$) are reported in Panel B and Panel C, respectively.

The estimates for the predictive coefficient $\beta_{Z,i}^{K_l}$ are reported with two-sided heteroskedasticity consistent p-values and adjusted R^2 (shown as $\bar{R}^2$). p-values corresponding to a 5% or better significance level are bolded. Bonferroni corrections based on three alternatives are applied. p-values corresponding to a significance level equal to, or better than, 3.3% after Bonferroni corrections are denoted with an asterisk. The sample period runs from January 1985 to December 2011.

Panel A. Predicting short-leg profits										
		month $t-1$			month $t-2$			month $t-3$		
Predictors (Z_{t-i})	Strategy K	$\beta_{Z,1}^{K_{short}}$	p	$\bar{R}^2$	$\beta_{Z,2}^{K_{short}}$	p	$\bar{R}^2$	$\beta_{Z,3}^{K_{short}}$	p	$\bar{R}^2$
r_{t-i}^{world}	1	0.07	0.11	0.3%	0.12	**0.03***	2.7%	0.00	0.94	-0.6%
r_{t-i}^{world}	2	0.04	0.21	-0.1%	0.10	**0.01***	2.3%	-0.02	0.54	-0.5%
r_{t-i}^{world}	3	0.04	0.26	-0.2%	0.10	**0.02***	2.3%	-0.03	0.48	-0.4%
$\Delta\sigma_{t-i}^{equity}$	1	0.05	0.93	-0.6%	-1.61	**<0.01***	4.7%	0.48	0.40	-0.2%
$\Delta\sigma_{t-i}^{equity}$	2	0.29	0.56	-0.4%	-1.44	**<0.01***	5.0%	0.62	0.19	0.4%
$\Delta\sigma_{t-i}^{equity}$	3	0.27	0.59	-0.4%	-1.49	**<0.01***	5.8%	0.62	0.19	0.5%
$\Delta\sigma_{t-i}^{FX}$	1	0.98	0.49	-0.4%	-3.84	**0.01***	2.9%	0.76	0.49	-0.5%
$\Delta\sigma_{t-i}^{FX}$	2	1.22	0.24	-0.2%	-2.74	**0.02***	1.8%	1.08	0.93	-0.2%
$\Delta\sigma_{t-i}^{FX}$	3	0.96	0.34	-0.3%	-2.55	**0.03**	1.6%	1.12	0.98	-0.2%

Panel B. Predicting long-leg profits

Predictors (Z_{t-i})	Strategy K	month $t-1$ $\beta_{Z,1}^{K_{long}}$	p	$\bar{R}^2$	month $t-2$ $\beta_{Z,2}^{K_{long}}$	p	$\bar{R}^2$	month $t-3$ $\beta_{Z,3}^{K_{long}}$	p	$\bar{R}^2$
r_{t-i}^{CRB}	1	0.13	0.08	0.9%	0.05	0.63	-0.1%	0.30	**<0.01***	5.7%
r_{t-i}^{CRB}	2	0.13	**0.05**	2.0%	0.06	0.44	1.0%	0.26	**<0.01***	6.8%
r_{t-i}^{CRB}	3	0.12	0.07	2.4%	0.05	0.55	1.3%	0.21	**<0.01***	5.6%
$\Delta\sigma_{t-i}^{equity}$	1	-0.35	0.55	0.0%	0.75	0.10	0.7%	-1.11	**0.03**	1.7%
$\Delta\sigma_{t-i}^{equity}$	2	-0.22	0.73	0.9%	0.50	0.20	1.2%	-1.03	**0.02***	2.9%
$\Delta\sigma_{t-i}^{equity}$	3	-0.27	0.66	1.3%	0.57	0.11	1.9%	-0.92	**0.01***	3.1%
$\Delta\sigma_{t-i}^{FX}$	1	-1.42	0.40	0.2%	-0.87	0.64	-0.1%	-3.00	0.10	1.4%
$\Delta\sigma_{t-i}^{FX}$	2	-1.63	0.25	1.4%	-0.19	0.90	0.7%	-2.95	**0.05**	2.8%
$\Delta\sigma_{t-i}^{FX}$	3	-1.65	0.23	1.9%	-0.01	0.99	1.1%	-2.25	0.07	2.5%

C. Predicting long/short profits

Predictors (Z_{t-i})	Strategy K	month $t-1$ $\beta_{Z,1}^{K_{long/sh}}$	p	$\bar{R}^2$	month $t-2$ $\beta_{Z,2}^{K_{long/shor}}$	p	$\bar{R}^2$	month $t-3$ $\beta_{Z,3}^{K_{long/sho}}$	p	$\bar{R}^2$
r_{t-i}^{CRB}	1	0.13	**0.04**	2.1%	0.15	**0.01***	2.8%	0.21	**0.01***	4.7%
r_{t-i}^{CRB}	2	0.12	**0.02***	1.9%	0.12	**0.01***	2.1%	0.17	**0.01***	4.3%
r_{t-i}^{CRB}	3	0.11	**0.03***	2.2%	0.10	**0.02***	2.3%	0.13	**0.01***	3.3%
$\Delta\sigma_{t-i}^{equity}$	1	-0.16	0.73	0.6%	-0.31	0.50	0.8%	-0.78	0.16	1.9%
$\Delta\sigma_{t-i}^{equity}$	2	-0.05	0.89	0.2%	-0.34	0.38	0.6%	-0.70	0.17	1.9%
$\Delta\sigma_{t-i}^{equity}$	3	-0.12	0.75	0.6%	-0.37	0.28	1.1%	-0.55	0.20	1.8%
$\Delta\sigma_{t-i}^{FX}$	1	-0.20	0.89	0.6%	-2.72	0.10	2.5%	-2.87	0.06	2.7%
$\Delta\sigma_{t-i}^{FX}$	2	-0.78	0.52	0.4%	-1.61	0.25	1.2%	-2.36	0.08	2.4%
$\Delta\sigma_{t-i}^{FX}$	3	-0.88	0.42	0.9%	-1.56	0.17	1.7%	-1.64	0.12	1.9%

Table 3.2 presents the estimation results for Equation (3). Although the empirical investigation of the predictability in each of the following three months is guided by the gradual information diffusion hypothesis (Hong and Stein, 1999, and Hong, Torous and Valkanov, 2007), it is unknown in which month the predictability will show up. Thus, data mining concerns need to be carefully addressed. One way to address this data mining concern is to use a very conservative Bonferroni approach and adjust the confidence level of the tests by the number of hypotheses tested. In the case here, the p −values of the tests should be tripled. Table 3.2 reports statistically significant results based on Bonferroni-adjusted significance levels at the 10% level or better (based on three models) with an asterisk, as well as normal 5% significance

levels. In Table 3, 26 out of the 32 significant slope estimates are robust to Bonferroni corrections, assuring us that the results are not due to data mining.[12]

The results in Table 3.2 shed light on the difference in predictability in the short and long leg of carry trades:

(1) Monthly MSCI World Equity Price Index return predicts carry trade profits from the short leg but not those from the long leg. Similarly, monthly changes in commodity prices predict the long-leg profits but not the short-leg profits. The predictive ability of monthly world equity index return shows up in two months' time, as demonstrated in the three significant slope estimates on r_{t-2}^{world} which have p-values below 0.05 (Panel A of Table 3.2). In contrast, the predictive power of monthly changes in commodity prices become significant in three months' time (shown as the three significant slope estimates on r_{t-3}^{CRB} with p-values below 0.05 in Panel B of Table 3.2). The existence of leg-specific predictors suggests that some predictable components in currencies are related to currency characteristics instead of common currency risk factors.

(2) The predictive effects from monthly changes in equity volatility ($\Delta\sigma_{t-i}^{equity}$) and monthly changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$) show up two months later in short-leg profits, demonstrated by the six significant slope estimates on $\Delta\sigma_{t-2}^{equity}$ and $\Delta\sigma_{t-2}^{FX}$ in Panel A of Table 3.2. In contrast, monthly changes in equity volatility and monthly changes in currency volatility only significantly predict long-leg carry trade profits in three months' time (shown as the four significant slope estimates on $\Delta\sigma_{t-3}^{equity}$ and $\Delta\sigma_{t-3}^{FX}$ in Panel B of Table 3.2). Why would two types of currencies react to changes in identical variables after different lengths of delay? The gradual information diffusion hypothesis by Hong and Stein (1999) provides one possible explanation. If more attention is paid to low-yielding currencies than to high-yielding currencies,

[12] I acknowledge that these predictors are motivated by a few recent studies and the importance of discovered predictors may be over-stated as a result of possible intergenerational data mining efforts.

information contained in predictors can be incorporated into low-yielding currencies first, before drastically affecting high-yielding currencies. For a U.S. investor, low-yielding currencies include the Japanese yen, the Swiss franc and sometimes the euro (and prior to that the Deutsche mark). These low-yielding currencies are far more actively traded currencies than high-yielding currencies, which typically include the Australian dollar, the New Zealand dollar and occasionally the British pound and Norwegian krone.[13] Hence, more attention might be paid to low-yielding currencies than to high-yielding currencies, leading to the different lengths in delays of investor reactions. Similar phenomena have been discovered in other asset markets where large firm stock returns lead small firms (Lo and MacKinlay, 1990), firms covered by more analysts lead the performance of firms with less analyst coverage (Hong, Kubik and Solomon, 2000) and the U.S. stock market leads other stock markets (Rapach, Strauss and Zhou, 2012) .

(3) These significant predictors of profits from each leg generally have weaker predictive power for combined profits from long/short strategies. For example, $\Delta\sigma_{t-2}^{equity}$ and $\Delta\sigma_{t-2}^{FX}$ ($\Delta\sigma_{t-3}^{equity}$ and $\Delta\sigma_{t-3}^{FX}$) significantly predict short (long) leg profits in month t, but lose their statistical significance for long/short profits. Also, r_{t-3}^{CRB} predicts long-leg profits more strongly than long/short profits, where the coefficients on r_{t-3}^{CRB} range between 0.21 and 0.30 for long-leg profits and between 0.13 and 0.21 for long/short profits, respectively.

Do these individually significant predictors lose their statistical significance in the presence of other predictors? The marginal effect is tested by including two predictors

[13] According to the 2010 triennial central bank survey conducted by the Bank of International Settlement, in April 2010, shares in global foreign exchange market turnover for the euro, the Japanese yen and the Swiss franc are 39.1%, 19.0% and 6.4%, respectively. The shares for the Australian dollar, the New Zealand dollar, the Norwegian krone and the British pound are 7.6%, 1.6%, 1.3% and 12.9%, respectively.

at a time in the model specified in Equation (3) and I present the results in Table 3.3.[14] There are three main findings regarding the two-predictor in-sample forecast. First, for the short-leg profit, $\Delta\sigma_{t-2}^{equity}$ remains a significant in-sample predictor in the presence of either r_{t-2}^{world} or $\Delta\sigma_{t-2}^{FX}$ (Panel A of Table 3.3). While $\Delta\sigma_{t-2}^{equity}$ appears to be a superior predictor for short-leg profits in-sample, the other two predictors demonstrate their merits in out-of-sample tests and economic significance tests to be discussed in the following sections. Second, for long-leg profits and long/short profits, r_{t-3}^{CRB} is a superior in-sample predictor, whose slope estimates all have p-values below 0.05 (Panel B and C in Table 3.3). Finally, while the significance of many strong single predictors drops when considered with an additional predictor, 23 out of the 27 joint p-values are below 0.05 in Table 3.3, demonstrating the good in-sample statistical significance of a large number of two-predictor combinations.

[14] The predictive ability of all possible combinations of two predictors at other monthly lags are also tested; the conclusion in this paper remains unchanged. Results are available upon request.

Table 3.3 Predicting carry trade profits in-sample with two predictors

This table reports results from predictive regression: $\overline{P}_t^{k_l} = \alpha + \beta_i\ Y_{t-i} + \gamma_i\ \overline{P}_{t-1}^{K_l} + \mu_t$

$(K = 1 \cdots 3, l = short, long\ and\ short/long)$,

where Y_{t-i} is a vector of two predictors, $\overline{P}_t^{K_l}$ denotes the profits from betting one U.S. dollar on K low-yielding currencies ($\overline{P}_t^{K_{short}}$), the profits from betting one U.S. dollar on K high-yielding currencies and the profits from betting half a U.S. dollar on each leg ($\overline{P}_t^{K_{long/short}}$).

The individual predictors for the short-leg carry trade profits are $\Delta\sigma_{t-i}^{equity}$, $\Delta\sigma_{t-i}^{FX}$ and r_{t-i}^{world}; and, the individual predictors for the long-leg carry trade profits and long/short carry trade profits are r_{t-i}^{CRB}, $\Delta\sigma_{t-i}^{equity}$ and $\Delta\sigma_{t-i}^{FX}$. Details of the predictors can be found in the main text. In order to conserve space, this table only reports results at a two-month lag ($i = 2$) for $\overline{P}_t^{K_{short}}$, and at a three-month lag ($i = 3$) for $\overline{P}_t^{K_{short}}$ and $\overline{P}_t^{K_{long/short}}$, when these predictive coefficients are individually significant.

The estimates for predictive coefficient β_i are reported with two-sided heteroskedasticity consistent p-values and adjusted R^2 (shown as $\bar{R}^2$). p-values less than 0.05 are denoted in bold font. The sample period runs from January 1985 to December 2011.

Panel A. Predicting short-leg profits in month t

Strategy K	$\boldsymbol{\beta_2}$ (r_{t-2}^{world})	p	$\boldsymbol{\beta_2}$ $(\Delta\sigma_{t-2}^{equity})$	p	$\boldsymbol{\beta_2}$ $(\Delta\sigma_{t-2}^{FX})$	p	Joint p	$\overline{R^2}$
1	0.07	0.15	-1.30	**<0.01**			**<0.01**	5.4%
2	0.05	0.19	-1.22	**<0.01**			**<0.01**	5.3%
3	0.05	0.23	-1.30	**<0.01**			**<0.01**	6.1%
1			-1.27	**<0.01**	-2.15	0.16	**<0.01**	5.3%
2			-1.27	**<0.01**	-1.05	0.39	**<0.01**	5.0%
3			-1.38	**<0.01**	-0.72	0.54	**<0.01**	5.7%
1	0.10	**0.06**			-3.11	**0.03**	**0.02**	4.6%
2	0.08	**0.03**			-2.12	0.06	**0.01**	3.3%
3	0.08	**0.04**			-1.95	0.08	**0.02**	3.2%

Panel B. Predicting long-leg profits in month t

Strategy K	$\boldsymbol{\beta_3}$ (r_{t-3}^{CRB})	p	$\boldsymbol{\beta_3}$ $(\Delta\sigma_{t-3}^{equity})$	p	$\boldsymbol{\beta_3}$ $(\Delta\sigma_{t-3}^{FX})$	p	Joint p	$\overline{R^2}$
1	0.27	**<0.01**	-0.70	0.09			**<0.01**	6.1%
2	0.24	**<0.01**	-0.67	0.06			**<0.01**	7.4%
3	0.18	**<0.01**	-0.64	0.06			**<0.01**	6.2%
1	0.19	**0.01**			-1.86	0.21	**<0.01**	6.0%
2	0.15	**0.02**			-1.94	0.13	**<0.01**	7.4%
3	0.11	**0.02**			-1.45	0.22	**<0.01**	5.9%
1			-0.80	0.09	-1.93	0.28	0.09	1.9%
2			-0.71	0.11	-2.00	0.21	**0.05**	3.3%
3			-0.71	0.08	-1.30	0.34	**0.04**	3.2%

Panel C. Predicting combined long/short strategy profits in month t

Strategy K	$\boldsymbol{\beta_3}$ (r_{t-3}^{CRB})	p	$\boldsymbol{\beta_3}$ ($\Delta\sigma_{t-3}^{equity}$)	p	$\boldsymbol{\beta_3}$ ($\Delta\sigma_{t-3}^{FX}$)	p	Joint p	$\overline{R^2}$
1	0.19	**0.01**	-0.51	0.25			**0.03**	4.9%
2	0.16	**0.02**	-0.48	0.26			**0.04**	4.7%
3	0.12	**0.02**	-0.39	0.32			**0.02**	3.5%
1	0.27	**<0.01**			-2.15	0.08	**0.01**	5.5%
2	0.24	**<0.01**			-1.75	0.11	**0.02**	5.1%
3	0.19	**<0.01**			-1.19	0.22	**0.01**	3.6%
1			-0.43	0.41	-2.31	0.14	0.16	2.7%
2			-0.42	0.41	-1.80	0.20	0.18	2.5%
3			-0.37	0.42	-1.15	0.32	0.24	2.0%

The signs of the significant slope estimates all make economic sense. First, for the short-leg profit, the slope estimates on r_{t-2}^{world} are all positive, in all single predictor and two-predictor regressions in Table 3.2 and Table 3.3. The positive slope estimate of r_{t-2}^{world} is a result of the rises of low-yielding currencies against the U.S. dollar following drops in world equity prices, leading to decreases in profits from shorting low-yielding currencies. This result is consistent with the intuition that after worldwide stock prices decrease, investors systematically buying safe-haven currencies. Second, the slope estimates for $\Delta\sigma_{t-2}^{equity}$ and $\Delta\sigma_{t-2}^{FX}$ ($\Delta\sigma_{t-3}^{equity}$ and $\Delta\sigma_{t-3}^{FX}$) are uniformly negative for predicting short- (long-) leg profits. A high level of average global equity volatility and global currency volatility predicts drops in profits from the short leg of carry trades two months later, as well as decreases in profits from the long leg of carry trades three months later. Finally, the slope coefficient estimates of r_{t-3}^{CRB} in predicting long-leg profits, and in predicting long/short profits are uniformly positive. The positive coefficient estimates suggest that past increases in commodity prices lead the appreciation of commodity currencies and increases in long-leg profits.

The size of predictive coefficients is of economic significance. For example, an increase of one standard deviation of r_{t-2}^{world} (4.59), $\Delta\sigma_{t-2}^{equity}$(0.44) and $\Delta\sigma_{t-2}^{FX}$(0.15) can lead to an annualized change of 5.35%, -7.94% and -4.69% in $\overline{P}_t^{3short}$ (the profit from shorting three low-yielding currencies), respectively. In standard deviation terms, these annualized changes in short-leg carry trade profits are 0.60, -1.90 and -0.50.

The in-sample R^2s in Table 3.2 and 3.3 appear to be comparable to those reported for predictability in carry trade profits (for example, Bakshi and Panayotov, 2012, Tables 2 and 3; Adrian, Etula and Shin, 2009, Tables 1 and 2). When the model uses a single predictor in month $t-2$ ($t-3$) to predict short- (long-) leg profits in month t, the adjusted R^2s range between 1.6% and 5.8% (1.4% and 6.8%). In predictive regressions for long/short profits with single predictors lagged three months, the adjusted R^2s range between 1.8% and 4.7%. When two of these predictors are used together at the same time, the adjusted R^2s range between 3.2% and 6.1% for short-leg profits, between 1.9% and 7.4% for long-leg profits and between 2.0% and 5.5% for long/short profits. In-sample adjusted R^2s from two-predictor regressions are generally higher than those from using single predictors.

An important question to ask is whether statistical inference in this paper is reliable in the presence of serial-correlations in explanatory variables. Although predictors in this paper are not highly persistent, to be sure, I gauge the reliability of the t-statistics using a pre-test derived by Campbell and Yogo (2006). More precisely, their pre-test shows that (Campbell and Yogo, 2006, p.35) inference from a conventional t-test is reliable when (1) the correlation of the disturbances' predictive regressions with the disturbances from a regression of the explanatory variable on itself lagged one period (which they call "delta") is sufficiently small (that is, with an absolute value below 0.125); or (2) if the absolute value of delta exceeds 0.125, the parameter c needs to be sufficiently negative[15] so that the predictor variable is stationary. In this study, absolute values of deltas for significant predictors range from

[15] c is calculated as $c = (\rho - 1) * T$, where r is the first-order autocorrelation of the explanatory variable and T equals the number of observations.

0.06 to 0.38 and parameter c values are all well below -200.[16] Comparing the values of delta and parameter c here with parameter values shown in Table 1 in Campbell and Yogo (2006), one can conclude that the inference from the t-statistics is reliable.

Carry trade profits from each leg and long/short strategies also correlate with these predictor variables contemporaneously (see Appendix 3.B.). How robust is this predictability in relation to the contemporaneous correlation of explanatory variables and carry trade profits? Also, many predictor variables lagged by two and three months significantly predict carry trades in month t. One may wonder how robust these predictability results are in relation to predictor variables in the immediate previous month(s). In order to answer these questions, regressions based on Equation (3) are re-estimated with additional controls, including the contemporaneous term of the explanatory variable and explanatory variables lagged by fewer months than in Equation (3). Discussed predictability results are robust to the inclusion of all other variables. The estimation results included in Appendix 3.F. remain qualitatively the same as in Table 3.3, suggesting the predictability in carry trades in this paper is not driven by contemporaneous changes in predictor variables.

Concluding this section, two messages are worth emphasizing. First, the in-sample results for profits from each leg suggest that predictors for short- and long-leg profits are different. It may be possible to deliver better forecasting by predicting short- and long-leg profits separately. Second, any combination of two predictors jointly and significantly predicts almost all dynamic carry trades, and in-sample adjusted R^2s from the regressions using two-predictors are generally higher than those from using single predictors. Thus, out-of-sample tests and economically significant tests are conducted using two-predictor regressions.[17]

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[16] Calculated from $\rho = 0.34$ (r_t^{CRB} has the highest first-order autocorrelation among all chosen predictors) and T=324. $c = (0.34 - 1) * 324$ =-214.

[17] Out-of-sample tests and economic significance tests using one predictor and two predictors are qualitatively the same and reported in Appendix 3.G and 3.H.

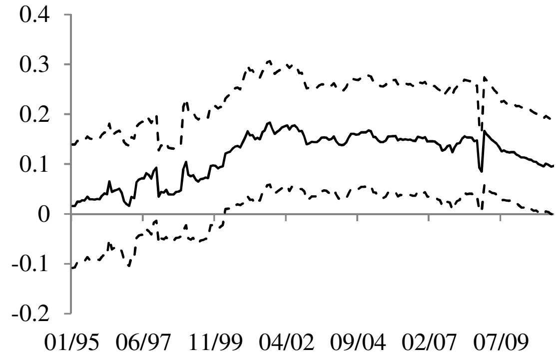
4. Rolling-window regressions

Carry trade investors suffered large losses in the 2008 financial crisis when the Australian dollar and the New Zealand dollar depreciated almost 30% in a month. It is reasonable to suspect that the significant full-sample result is driven by a few extreme observations during a certain period. This section partially addresses this concern by running 10-year rolling-window regressions using Equation (3), and plotting the slope estimates over time in Figure 3.2**.** The slope estimates on the MSCI World Equity Price Index return two months ago appear to consistently positively predict short-leg profits in this month (Panel A of Figure 3.2). Similarly, changes in the commodity index lagged by three months appear to consistently positively predict long-leg monthly profits (Panel D of Figure 3.2). In contrast, changes in equity volatility and changes in currency volatility do not always negatively predict future carry trade profits from the long leg and stayed in the positive regime for a few years after 2000. Out-of-sample tests in the following section will complement the rolling-window analysis.

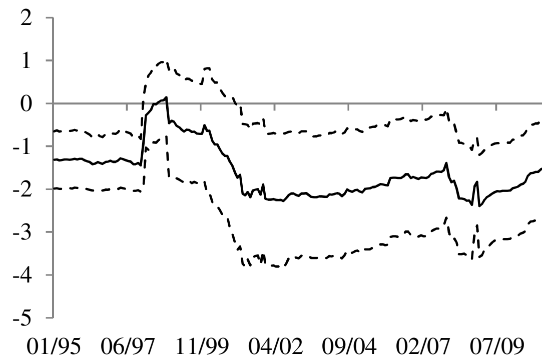
Figure 3.2 Rolling-window regressions: predicting carry trade profits

Predictive slope estimates from rolling predictive regressions as specified in Equation (3) are plotted across time. To conserve space, this figure includes only plots of rolling-window predictive betas whose full-sample counterparts are significant for the three-currency strategy (strategy 3). The solid line represents the slope estimates and the dashed lines represent 90% confidence bands.

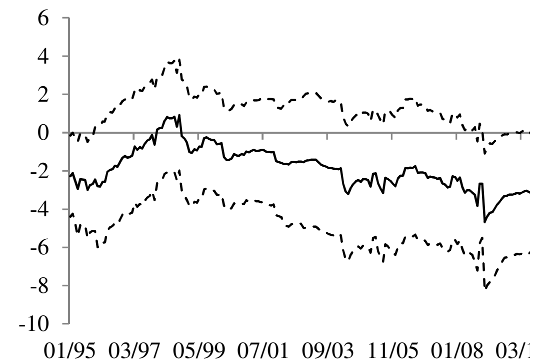
A. Predicting the profits from short-leg: slope estimates on r_{t-2}^{world}



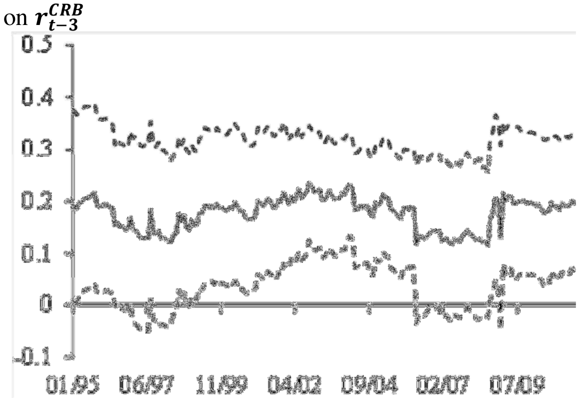
B. Predicting the profits from short-leg: slope estimates on $\Delta\sigma_{t-2}^{equity}$



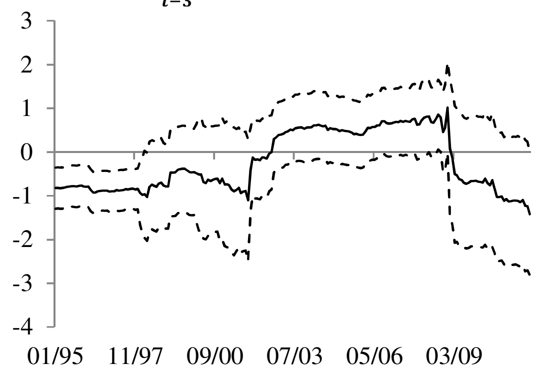
C. Predicting the profits from short-leg: slope estimates on $\Delta\sigma_{t-2}^{FX}$



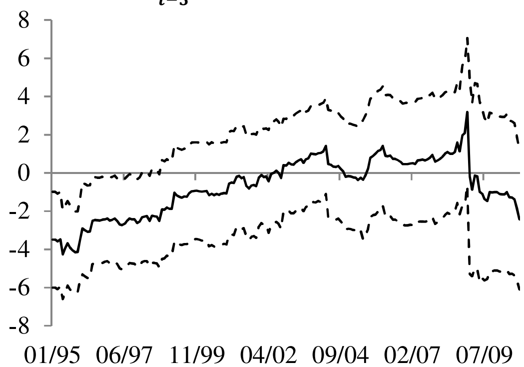
D. Predicting the profits from long-leg: slope estimates on $\boldsymbol{r_{t-3}^{CRB}}$



E. Predicting the profits from long-leg: slope estimates on $\boldsymbol{\Delta\sigma_{t-3}^{equity}}$



F. Predicting the profits from long-leg: slope estimates on $\boldsymbol{\Delta\sigma_{t-3}^{FX}}$



5. Out-of-sample evidence on predictability in carry trade profits

Could an investor have used these prediction models to deliver better forecasting than simply using historical means? In order to answer this question, this paper relies on out-of-sample (OoS) R^2 statistics as in Goyal and Welch (2008). The $OoS\ R^2$ is computed as follows:

$$OoS\ R^2 = 1 - \frac{MSE(prediction\ model)}{MSE(benchmark\ model)} = 1 - \frac{\sum_{j=1}^{n}(\widehat{\theta_t} - \overline{P}_t)^2}{\sum_{j=1}^{n}(\theta_t - \overline{P}_t)^2}, \tag{4}$$

where $\widehat{\theta_t}$ is the predicated carry trade profit in month t and θ_t is the historical average profit. $\overline{P}_t$ is the realized carry trade profit in month t. A positive $OoS\ R^2$ indicates that the prediction model generates a lower mean-squared prediction error than that from the prediction based on historical means, or from outperforming the benchmark model.

Further, if there is outperformance, is it statistically significant? A test for significance of forecast improvement is conducted using an adjusted mean-squared prediction error statistic (MSPE-adjusted) developed by Clark and West (2007). The MSPE-adjusted one-sided p-values are obtained by regressing $f_t = (\overline{P}_t - \theta_t)^2 - [\left(\overline{P}_t - \widehat{\theta_t}\right)^2 - \left(\theta_t - \widehat{\theta_t}\right)^2]$ on a constant. The null hypothesis is that there is no significant improvement in prediction. Thus, a lower p-value indicates higher significance of outperformance.

An investor could have used the model specified in Equation (3) and observations available prior to month t to predict carry trade profits in month t ($\widehat{\theta_t}$). Alternatively, he or she could simply use the average of carry trade profits prior to month t as a prediction (θ_t). First, this investor uses observations in the first 180 months of the sample to make the first prediction. Next, the prediction model is re-estimated every month using all historical observations to predict the one-month-ahead carry trade profit. Then, $OoS\ R^2$'s and MSPE-adjusted one-sided p-values are computed to evaluate the model predictions against the historical means.

Table 3.4 presents the $OoS\ R^2$ and corresponding MSPE-adjusted one-sided p-values obtained using two predictors. If an investor uses these leg-specific prediction models to predict carry trade profits, he or she can predict profits from each leg with a different model, or the investor can use a single model to predict long/short profits. If an investor uses different models to predict profits on each leg and then aggregates them into predictions for long/short profits, the $OoS\ R^2$ ranges between 6.3% and 15.4% (Panel D of Table 3.5), which is more than double the $OoS\ R^2$s from predicting long/short profits with a single model, as shown in Panel C of Table 3.5. These $OoS\ R^2$s appear comparable to those reported for carry trade predictability by Bakshi and Payayotov (2012), and they tend to be higher than those reported for the equity market (for instance, in Goyal and Welch, 2008; Campbell and Thompson, 2008; Rapach, Strauss and Zhou, 2012). Turning to the MSPE-adjusted one-sided p-values, the out-of-sample predictability is also evident, in that 35 out of 36 p-values are below 0.1 in Table 3.5.

Table 3.4 Out-of-sample performance of carry trade profits predictors

This table reports out-of-sample R^2s (Goyal and Welch, 2007) for predicting carry trade profits with two predictors and MSPE-adjusted one-sided p-values (Clark and West, 2007). The predicted variable is monthly carry trade profits $\overline{P}_t^{kl}$ ($k = 1 \cdots 3,\ l = short, long, long/short$) , where $\overline{P}_t^{K_{long/short}}$ is the profits of carry trade strategies with k long and short positions and $\overline{P}_t^{long_K}$ ($\overline{P}_t^{short_K}$) is profits from carry trade strategies with k long (short) positions only. The sample period is from January 1985 to December 2011. The first 180 monthly observations are used to estimate the prediction models and forecast the first one-month-ahead carry trade profits, then models are re-estimated every month using all past observations to predict carry trade profits in a new month.

The $OoS\ R^2$ is computed as in Goyal and Welch (2007):

$$OoS\ R^2 = 1 - \frac{MSE(prediction\ model)}{MSE(benchmark\ model)} = 1 - \frac{\sum_{j=1}^{n}(\widehat{\theta_t} - \overline{P}_t\ )^2}{\sum_{j=1}^{n}(\theta_t - \overline{P}_t\ )^2}\ ,$$

where $\widehat{\theta_t}$ is the predicted carry trade profit in month t and θ_t is the historical average profit. $\overline{P}_t$ is the realized carry trade profit in month t.

The MSPE-adjusted one-sided p-values are obtained by regressing $f_t = (\overline{P}_t^{k_j} - \theta_t)^2 - [\left(\overline{P}_t^{k_j} - \widehat{\theta_t}\right)^2 - \left(\theta_t - \widehat{\theta_t}\right)^2]$ on a constant.

Panel A. Predicting short-leg profits in month t

		Predictors		
$OoS\ R^2$ (%)		$r_{t-2}^{world} + \Delta\sigma_{t-2}^{FX}$	$r_{t-2}^{world} + \Delta\sigma_{t-2}^{equity}$	$\Delta\sigma_{t-2}^{FX} + \Delta\sigma_{t-2}^{equity}$
	Strategy K			
	1	7.6	7.2	6.2
	2	5.3	5.8	5.0
	3	5.0	5.8	5.0
MSPE-adjusted one-sided p-values				
	1	0.08	0.07	0.08
	2	0.07	0.05	0.06
	3	0.08	0.05	0.06

Panel B. Predicting long-leg profits in month t

		Predictors		
$OoS\ R^2$ (%)		$r_{t-3}^{CRB}+\Delta\sigma_{t-3}^{equity}$	$r_{t-3}^{CRB}+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}+\Delta\sigma_{t-3}^{FX}$
	Strategy K			
	1	6.8	6.7	1.7
	2	7.4	7.0	2.1
	3	5.7	5.0	1.4
MSPE-adjusted one-sided p-values				
	1	0.05	0.05	0.06
	2	0.04	0.04	0.08
	3	0.03	0.04	0.16

Panel C. Predicting long/short profits in month t with a single model

		Predictors		
$OoS\ R^2$ (%)		$r_{t-3}^{CRB}+\Delta\sigma_{t-3}^{equity}$	$r_{t-3}^{CRB}+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}+\Delta\sigma_{t-3}^{FX}$
	Strategy			
	1	7.7	8.8	3.2
	2	5.8	6.2	2.3
	3	4.7	4.6	1.7
MSPE-adjusted one-sided p-values				
	1	0.02	0.02	0.03
	2	0.01	0.02	0.05
	3	0.01	0.01	0.07

Panel D. Predicting long/short profits in month t with a different model for each leg (Strategy 1)

$OoS\ R^2$ (%)

	Long-leg predictors		
Short-leg predictors	r_{t-3}^{CRB}+$\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB}+$\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$+$\Delta\sigma_{t-3}^{FX}$
$r_{t-2}^{world} + \Delta\sigma_{t-2}^{FX}$	15.4	15.4	6.8
$r_{t-2}^{world} + \Delta\sigma_{t-2}^{equity}$	14.9	14.8	6.3
$\Delta\sigma_{t-2}^{FX} + \Delta\sigma_{t-2}^{equity}$	15.2	15.2	6.4

MSPE-adjusted one-sided p-values

	Long-leg predictors		
Short-leg predictors	r_{t-3}^{CRB}+$\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB}+$\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$ + $\Delta\sigma_{t-3}^{FX}$
$r_{t-2}^{world} + \Delta\sigma_{t-2}^{FX}$	0.03	0.03	<0.01
$r_{t-2}^{world} + \Delta\sigma_{t-2}^{equity}$	0.03	0.03	<0.01
$\Delta\sigma_{t-2}^{FX} + \Delta\sigma_{t-2}^{equity}$	0.03	0.03	<0.01

6. Economic significance

Could an investor have used the predictability in each leg to improve his or her profits from dynamic carry trades? The impact of a one standard deviation change in the predictors has been considered already. Here, first trading outcomes of market-timing strategies based on predictions from model (3) are compared with those from simple carry trade strategies, where one stays fully invested in carry trades. In a market-timing strategy, the trading decision is based on one-step-ahead prediction of carry trade profits. An investor goes ahead with a carry trade if the predicted profit is positive; otherwise, he or she refrains from a carry trade. This decision rule can first be applied to each leg of a carry trade. The related outcomes are reported in Panels A and B of Table 3.5. An investor can make trading decisions based on predicted long/short profits from a single model and decide to either establish positions on both legs, or stay away from carry trades (*long/short market-timing strategy*). The trading outcome is reported in Panel C of Table 3.5. Alternatively, if the investor predicts profits from each leg with a different model, he or she can make independent trading decisions for each leg (*two-legged marking-timing strategy*). Trading outcomes from each leg are then aggregated into profits to the two-legged market-timing strategy.

Only trading outcomes from the two-legged market-timing strategies using one currency on each leg (strategy 1) are reported in Panel D of Table 3.5, in order to conserve space.[18]

Comparing profits from market-timing strategies with the sample strategies, one can see improvements in the mean, Sharpe-ratios and skewness across the board. The scale of improvement is most noticeable for the two-legged market-timing strategies (Panel D of Table 3.5). Mean profits from these one-currency two-legged market-timing strategies range between 7.24% and 9.16% per annum, annualized Sharpe-ratios range between 0.76 and 1.09 and skewness ranges between -0.07 and 0.52. These ranges are higher than comparable statistics for the simple carry trade strategy with one currency on each leg (strategy 1), which has an average annual profit of 5.76%, annualized Sharpe ratio of 0.53 and skewness of -0.56. Equally important, outcomes from these two-legged market-timing strategies also compare favourably with outcomes from long/short market-timing strategies (comparable results for using one currency on each leg are shown on the first of row of Panel C of Table 3.5).

How statistically significant are these improvements? The statistical significance of the outperformance of market-timing strategies is obtained through 20,000 trials of moving block bootstrapping, where the block size is set at $N^{1/4}$, based on the blocking rule recommended by Hall, Horowitz and Jing (1995) for a one-sided test. A p-value is computed as the proportion of total bootstrap trials for which the mean, the Sharpe ratio and skewness of a market-timing strategy is worse (lower for mean and Sharpe-ratio, or more negatively skewed) than those from a simple carry trade strategy. In square brackets, reported are p-values against the null that a market-timing strategy does not outperform the corresponding simple carry trade strategy. In curly brackets are the p-values against the null that a two-legged market-timing strategy does not outperform the corresponding market-timing strategy based on one decision rule. Profit profiles of simple carry trade strategies are also shown in the

[18] Results for the other two strategies are similar.

same table to facilitate comparisons. The first main finding is that the outperformance versus simple carry trade strategies is most statistically significant for two-legged market-timing strategies. Related p-values, shown in the square brackets in Panel D of Table 3.5, suggest that the mean profits, Sharpe-ratios and skewness significantly improved in five out of nine cases, in all nine cases and in five out of nine cases, respectively. The out-performance of the two-legged market-timing strategies over long/short market-timing strategies is also significant. As shown in curly brackets in Panel D of Table 3.5, there are statistically significantly improvements in mean profits, Sharpe ratios and skewness in five out of nine cases, five out of nine cases and three out of nine cases, respectively.

In summary, the outperformance of the two-legged market-timing strategies highlights the economic relevance of difference in predictability identified for the short and long leg of carry trades. It appears that one can improve carry trade profits, their Sharpe-ratios and the skewness by separately making trade decisions for the short and long leg of carry trades. Such tangible economic value further strengthens the in-sample and out-of-sample predictability results.

Table 3.5 Economic significance – profits from market-timing strategies

This table reports the annual mean, Sharpe ratio and skewness of monthly profits from market-timing strategies conditional on predicted carry trade. In Panels A, B and C, the predictors are shown as column heads. In Panel D, the predictors for the long-leg profits are shown as column heads and the predictors for the short-leg profits are shown as row heads. Using the market-timing carry trade strategy, one goes ahead with the carry trade if the predicted profits are positive and does nothing otherwise. The sample period is from January 1985 to December 2011. The first 180 monthly observations are used to estimate prediction models and forecast the first one-month-ahead carry trade profits, then models are re-estimated every month using all past observations to predict carry trade profits in a new month. In square brackets are the p-values against the null that market-timing strategies do not outperform a simple carry trade strategy. In curly brackets are the p-values against the null that strategies-based separate decision rules for each leg of carry trade outperform strategies based on one decision rule for combined long/short-leg profits. p-values are obtained through 20,000 trials of bootstrap using a block size of $N^{1/4}$, based on the blocking rule recommended by Hall, Horowitz and Jing (1995) for a one-sided test. p-values lower than 10% are denoted in bold font. In order to facilitate comparison, statistics related to simple dynamic carry trade strategies are reported again.

Panel A. Short-leg profits conditioned on model prediction

	Mean (annual)				Sharpe Ratio (annual)				Skewness (monthly)			
Strategy	Simple	$r^{world}_{t-2} + \Delta\sigma^{FX}_{t-2}$	$r^{world}_{t-2} + \Delta\sigma^{equity}_{t-2}$	$\Delta\sigma^{FX}_{t-2} + \Delta\sigma^{equity}_{t-2}$	Simple	$r^{world}_{t-2} + \Delta\sigma^{FX}_{t-2}$	$r^{world}_{t-2} + \Delta\sigma^{equity}_{t-2}$	$\Delta\sigma^{FX}_{t-2} + \Delta\sigma^{equity}_{t-2}$	Simple	$r^{world}_{t-2} + \Delta\sigma^{FX}_{t-2}$	$r^{world}_{t-2} + \Delta\sigma^{equity}_{t-2}$	$\Delta\sigma^{FX}_{t-2} + \Delta\sigma^{equity}_{t-2}$
1	-1.74	1.71	0.33	-0.13	-0.20	0.29	0.05	-0.02	-1.08	0.88	0.35	0.28
2	-1.45	1.10	-0.32	-0.11	-0.19	0.19	-0.05	-0.02	-0.38	0.48	0.36	0.36
3	-1.93	0.67	-1.16	-0.55	-0.25	0.11	-0.19	-0.09	-0.34	0.50	0.28	0.39
1		**[0.02]**	**[0.10]**	**[0.15]**		**[0.01]**	[0.11]	[0.18]		**[<0.01]**	**[0.04]**	**[0.05]**
2		**[0.03]**	[0.18]	[0.13]		**[0.02]**	[0.22]	[0.16]		**[0.05]**	**[0.05]**	**[0.04]**
3		**[0.02]**	[0.26]	[0.13]		**[0.02]**	[0.33]	[0.18]		**[0.05]**	[0.12]	**[0.07]**

Panel B. Long-leg profits conditioned on model prediction

	Mean (annual)				Sharpe Ratio (annual)				Skewness (monthly)			
Strategy	simple	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$ $+\Delta\sigma_{t-3}^{FX}$	simple	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$ $+\Delta\sigma_{t-3}^{FX}$	simple	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$ $+\Delta\sigma_{t-3}^{FX}$
1	9.08	10.17	10.48	9.47	0.68	0.88	0.88	0.76	-0.60	-0.39	-0.38	-0.40
2	7.47	9.01	9.93	7.81	0.60	0.85	0.89	0.66	-0.52	-0.43	-0.40	-0.36
3	5.80	7.34	8.36	5.87	0.52	0.77	0.87	0.55	-0.74	-0.84	-0.69	-0.79
1		[0.29]	[0.18]	[0.39]		[0.11]	**[0.08]**	[0.29]		[0.23]	[0.17]	[0.18]
2		[0.22]	[0.03]	[0.42]		**[0.06]**	**[<0.01]**	[0.32]		[0.37]	[0.33]	[0.13]
3		[0.20]	[0.05]	[0.51]		**[0.06]**	**[0.01]**	[0.38]		[0.56]	[0.40]	[0.62]

Panel C. Long/short profits conditioned on predictions from a single model

	Mean (annual)				Sharpe Ratio (annual)				Skewness (monthly)			
Strategy	simple	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$ $+\Delta\sigma_{t-3}^{FX}$	Simple	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$ $+\Delta\sigma_{t-3}^{FX}$	simple	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$ $+\Delta\sigma_{t-3}^{FX}$
1	5.76	8.01	8.03	6.01	0.53	0.90	0.83	0.62	-0.56	0.01	-0.05	-0.17
2	4.99	6.46	6.47	3.93	0.50	0.81	0.72	0.43	-0.03	0.68	0.46	-0.38
3	3.54	4.94	4.48	2.77	0.40	0.66	0.53	0.34	0.01	0.42	0.15	-0.24
1		[0.14]	[**0.07**]	[0.45]		**[0.06]**	**[0.05]**	[0.31]		[0.16]	[0.14]	[0.27]
2		[0.21]	[0.11]	[0.84]		**[0.07]**	**[0.08]**	[0.79]		[0.14]	[0.13]	[0.89]
3		[0.19]	[0.16]	[0.81]		**[0.09]**	[0.13]	[0.75]		[0.19]	[0.15]	[0.89]

Panel D. Long/short profits where profits from each leg are conditioned on predictions from a different models

Strategy 1	Mean (annual)			Sharpe ratio (annual)			Skewness (monthly)		
	Long-leg predictors			Long-leg predictors			Long-leg predictors		
Short-leg predictors	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$ $+\Delta\sigma_{t-3}^{FX}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$ $+\Delta\sigma_{t-3}^{FX}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{equity}$	r_{t-3}^{CRB} $+\Delta\sigma_{t-3}^{FX}$	$\Delta\sigma_{t-3}^{equity}$ $+\Delta\sigma_{t-3}^{FX}$
$r_{t-2}^{world} + \Delta\sigma_{t-2}^{FX}$	8.91	9.16	8.16	1.09	1.01	0.88	0.52	0.28	0.17
$r_{t-2}^{world} + \Delta\sigma_{t-2}^{equity}$	8.22	8.48	7.47	0.95	0.89	0.77	0.12	0.01	-0.06
$\Delta\sigma_{t-2}^{FX} + \Delta\sigma_{t-2}^{equity}$	7.99	8.24	7.24	0.94	0.88	0.76	0.11	0.01	-0.07
$r_{t-2}^{world} + \Delta\sigma_{t-2}^{FX}$	**[0.07]**	**[0.01]**	**[0.05]**	**[<0.01]**	**[<0.01]**	**[0.01]**	**[0.03]**	**[0.02]**	**[0.03]**
$r_{t-2}^{world} + \Delta\sigma_{t-2}^{equity}$	[0.13]	**[0.05]**	[0.14]	**[0.03]**	**[0.03]**	**[0.09]**	[0.13]	**[0.09]**	[0.13]
$\Delta\sigma_{t-2}^{FX} + \Delta\sigma_{t-2}^{equity}$	[0.15]	**[0.07]**	[0.18]	**[0.04]**	**[0.04]**	**[0.10]**	[0.14]	**[0.10]**	[0.14]
$r_{t-2}^{world} + \Delta\sigma_{t-2}^{FX}$	**{0.10}**	**{0.10}**	**{0.01}**	**{0.03}**	**{0.05}**	**{<0.01}**	**{0.01}**	**{0.06}**	**{0.04}**
$r_{t-2}^{world} + \Delta\sigma_{t-2}^{equity}$	{0.36}	{0.29}	**{0.06}**	{0.28}	{0.26}	**{0.05}**	{0.13}	{0.25}	{0.18}
$\Delta\sigma_{t-2}^{FX} + \Delta\sigma_{t-2}^{equity}$	{0.50}	{0.39}	**{0.09}**	{0.31}	{0.30}	**{0.07}**	{0.18}	{0.27}	{0.20}

7. Gradual information diffusion?

At the first sight, an under-reaction story for the discovered predictability appears implausible, because world equity prices, commodity prices, equity volatility and currency volatility are all public information. The gradual information diffusion hypothesis put forward by Hong and Stein (1999) and Hong, Torous and Valkanov (2007) stands out as a most likely explanation. They show that gradual information diffusion can lead to cross-asset return predictability, for instance, when investors in one asset market do not pay attention to information in other asset markets, or when investors wake up to information at different points in time.

What does the gradual information diffusion hypothesis imply for the observed predictability in carry trades in this study? Changes in world equity prices are closely related to economic outlook. The impact of equity price changes on carry trade profits is, however, not always straightforward, and investors may react at different points in time to information in the equity price change. If investors always interpret equity price increases as indicating a better economic outlook, they would immediately increase their borrowing in low-interest currencies and aggressively invest in risk assets (for example, emerging market equities and bonds, high-yield bonds, commodities and commodity currencies); hence, there should not have been any predictability in low-yielding currencies from the world equity index return. In reality, however, equity price increases do not necessary equate to a better economic outlook. Rises in equity prices can also signal a growing bubble inflated by investors' irrational exuberance (Shiller, 2001), or by the cheap funding provided by governments' economic stimulus packages.[19] As it is not trivial to make the judgement that the general economic outlook has improved, currency investors can react with a delay to information in equity prices. Hence, world equity price rises (drops) predict low-yielding currencies' depreciation (appreciation) and increases (decreases) in the short-leg carry trade profit. Similarly, currency investors can also

[19] See the article, "Mother of all carry trades faces an inevitable bust", by Nouriel Roubini published in *The Financial Times* on November 1, 2009.

react to information in commodity prices, equity volatility and currency volatility with delays, and not necessarily at the same time.

7.1. Predictive power and lengths of lags between predictors and carry trade profits

The results in Section 3.2 show that the predictability in the short and long legs of carry trades has a delay of one and two months, respectively. One does not know, however, whether the lengths of the delays are exactly one and two months. This study follows Driesprong, Jacobsen and Maat (2008) and conducts an additional test for the gradual information diffusion hypothesis, for each leg of carry trades. They argue that if investors react with a delay to information in the predictors, the predictability effect should become stronger once a lag is introduced between carry trade profits and the predictors; the predictability effects should also peak and decrease quickly as the lag size increases. First, a lag of one week (containing five trading days) is introduced between the long and short carry trade profits and each predictor before running the regression specified in Equation (5). Then, the procedure is repeated for different lag sizes up to 12 weeks.

$$\overline{P}_t^{k_l} = \alpha + \beta_1 \; Z_{t-1} + \mu_t \;\; (k = 1 \cdots 3,\; l = short, long), \tag{5}$$

where $\overline{P}_t^{k_l}$ is the short-leg profit, or long-leg profit, from each of the three strategies (six profits in total), and Z_{t-1} is a single predictor in the previous month.

Figure 3.3 Explanatory powers with different lag sizes

The figure depicts the $\boldsymbol{R^2}$ the regression specified in Equation (5), with different lag sizes between the predictors and carry trade profits. $\overline{\boldsymbol{P}}_{\boldsymbol{t}}^{\boldsymbol{k_l}} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\, \boldsymbol{Z_{t-1}} + \boldsymbol{\mu_t}\ \ (\boldsymbol{k = 1 \cdots 3},\ \boldsymbol{l = short, long})$, (5)

where $\overline{P}_t^{k_l}$ is the short-leg profit or long-leg profit from each of the three strategies (six profits in total), and Z_{t-1} is a single predictor in the previous month. The individual predictors for the short-leg carry trade profit are $\Delta\sigma_{t-1}^{equity}$, $\Delta\sigma_{t-1}^{FX}$ and r_{t-1}^{world}. The individual predictors for the long-leg carry trade profit include $\Delta\sigma_{t-1}^{equity}$, $\Delta\sigma_{t-1}^{FX}$ and r_{t-1}^{CRB}. The sample period is January 1985 to December 2011. R^2s from the predictive regressions for profits from strategy 1 (one currency on each leg) are plotted across time. Results for the other two strategies exhibit similar patterns.

A. Predicting short-leg carry trades B. Predicting long-leg carry trades

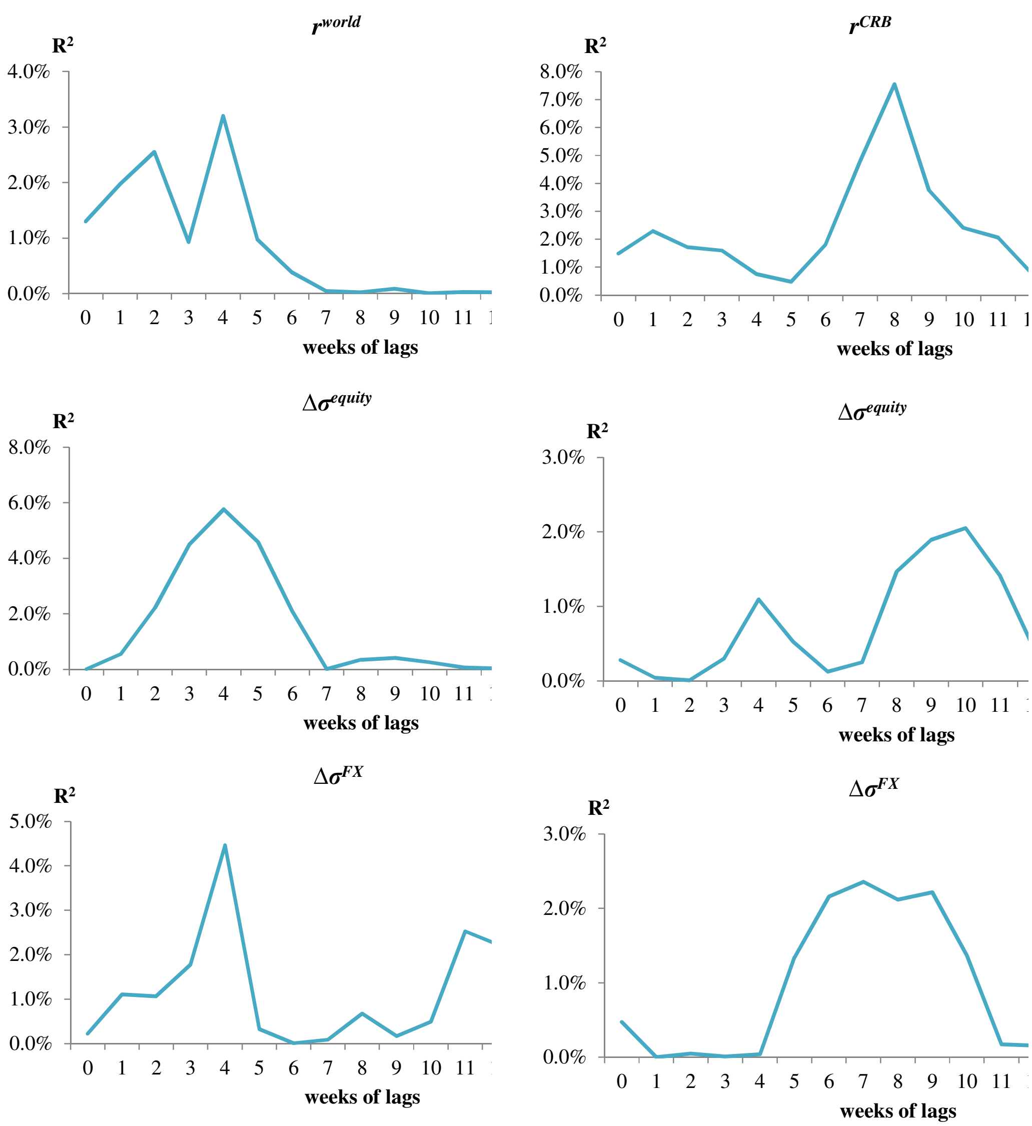


Figure 3.3 plots the R^2 as a function of different numbers of weeks used as lags, from predictive regressions where dependent variables are short- and long-leg profits from strategy 1 (one currency on each leg). As the results are qualitatively similar for the other strategies, only the results for strategy 1 are reported. The first interesting pattern is that R^2s peak at different lags for the short leg and long leg of carry trades. For the short leg (charts on the left), the predictive regressions have their highest explanatory power for a lag of four weeks. By contrast, predictive regressions for the long-leg carry trade profit have the highest R^2s for a lag between eight to 10 weeks (charts on the right). For lags longer than four weeks (eight to 10 weeks), the explanatory power for the profits from selling low-yielding currencies short (buying high-yielding currencies forward) quickly decreases. These results provide further support for the gradual information diffusion hypothesis.

7.2. Predictors and macro-economic fundamentals

This section shows that the variables predicting carry trade profits contain information about market fundamentals, as proxied for by industrial growth in the OECD countries. Carry trades, like stock investments, demonstrate a cyclical nature and long-run predictability driven by proxies for economic activities such as industrial production growth, as demonstrated in a study by Lustig, Roussanov, Verdelhan and Sloan (2012). Thus, in the context of carry trades, a testable prediction from the gradual information diffusion model in Hong, Torous and Valkanov (2007, p. 372) is that a variable's ability to predict carry trade profits ought to be correlated with its ability to forecast indicators of market fundamentals, as proxied for by the OECD industrial production growth. Following the test in Hong, Torous and Valkanov (2007), it is first necessary to forecast OECD industrial production growth ΔIP_t^{OECD}:

$$\Delta IP_t^{OECD} = \varphi_i + \lambda_{Z,i} Z_{t-i} + \sum_{s=1}^{3} \xi_s \, \Delta IP_{t-s}^{OECD} + \omega_t \; (i = 1 \cdots 3) \,, \qquad (6)$$

where Z_{t-i} is the value of predictor Z_t in month $t-i$ and control variables include industrial production growth in each of the previous three months. The predictors include eight of the nine predictors investigated by this paper (except ΔIP_t^{OECD} itself), which include changes in equity volatility ($\Delta\sigma_t^{equity}$), changes in currency volatility ($\Delta\sigma_t^{FX}$), the world index return (r_t^{world}), changes in a commodity index (r_t^{CRB}), changes in global liquidity (Δliq_t), changes in the VIX index (ΔVIX_t), changes in term structure ($term_t$) and changes in the average forward discounts (AFD_t). A detailed description and motivation of these predictors can be found in Appendix 3.B.

The coefficients of interest are $\lambda_{Z,i}{}'s$, which measure the ability of each variable to predict industrial production growth. If the variables that can strongly forecast carry trade profits from each leg (as measured by $\beta_{Z,i}^{K_l}{}'s$ from Equation (3)) also forecast market fundamentals, the relationship between $\beta_{Z,i}^{K_l}{}'s$ and $\lambda_{Z,i}{}'s$ is expected to be positive. In other words, variables such as monthly changes in commodity prices lagged by three months which positively predicts monthly long-leg profits (or, $\beta_{Z,3}^{K_{long}}$) ought to also have a positive λ_3. It turns out to be indeed the case. First, I obtain estimates for $\beta_{Z,2}^{3_{short}}{}'s$ and $\beta_{Z,3}^{3_{long}}{}'s$, using each of the above eight predictors. Here, the length of lag, i is chosen to be two and three, for the short leg and for the long leg, respectively, in order to be consistent with discovered predictability in each leg. In order to visualise the relation between $\lambda_{Z,2}{}'s$ and $\beta_{Z,2}^{K_{short}}{}'s$ and that between $\lambda_{Z,3}{}'s$ and $\beta_{Z,3}^{K_{long}}{}'s$, I plot them in two charts in Figure 3.4. If the discussed predictability is un-related to gradual flow of information related to economic fundamentals, we should not see any relation between $\lambda_{Z,2}{}'s$ and $\beta_{Z,2}^{K_{short}}{}'s$, or between $\lambda_{Z,3}{}'s$ and $\beta_{Z,3}^{K_{long}}{}'s$. Contrarily, there is a clear positive relation between the $\lambda_{Z,2}{}'s$ and $\beta_{Z,2}^{K_{short}}{}'s$ and the $\lambda_{Z,3}{}'s$ and $\beta_{Z,3}^{K_{long}}{}'s$. A straight line is fitted in Figure 3.4 by running an OLS regression of $\lambda_{Z,2}{}'s$ and $\beta_{Z,2}^{K_{short}}{}'s$ and $\lambda_{Z,3}{}'s$ and $\beta_{Z,3}^{K_{long}}{}'s$. The slope coefficient is 1.21 (0.90) when using variables lagged by two months (three months) to predict short-leg profits (long-leg profits) with a t-stat of 5.68 (3.89). That is, there is a strong positive correlation between the ability of a variable to forecast carry trade profits and its ability to forecast industrial production growth.

Figure 3.4 Predicting ΔIP_t^{OECD} and predicting carry trade profits

This figure include plots that depict the relationship between a variable's ability to predict carry trade profits (measured by $\beta_{Z,i}^{K_l}$) and its ability to predict OECD industrial production growth (measured by $\lambda_{Z,i}$). $\beta_{Z,i}^{K_l}$ denotes the predictive coefficient on predictor Z_{t-i}, for profits from the leg l (l=long, short, long/short) of carry trade strategy K (using K currencies). $\lambda_{Z,i}$ denotes the predictive coefficient on predictor Z_{t-i}, for the OECD industrial production growth (ΔIP_t^{OECD}).

Z is one of the eight of the nine predictors investigated by this paper (except ΔIP_t^{OECD} itself) which include changes in equity volatility ($\Delta\sigma_t^{equity}$), changes in currency volatility ($\Delta\sigma_t^{FX}$), the world index return (r_t^{world}), changes in a commodity index (r_t^{CRB}), changes in global liquidity (Δliq_t), changes in the VIX index (ΔVIX_t), changes in term structure ($term_t$) and changes in the average forward discounts (AFD_t). A detailed description and motivation of these predictors can be found in Appendix 3.B.

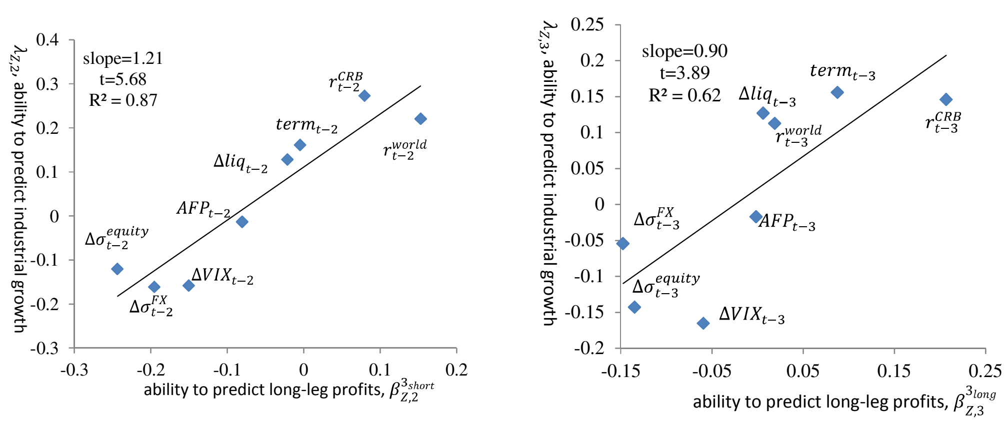
First, profits from Strategy 3 ($K = 3$), where three currencies are bought or sold forward on each leg, are regressed on each of the eight predictors, in order to obtain estimates for $\beta_{Z,2}^{3short}{}'s$ and $\beta_{Z,3}^{3long}{}'s$. Here, the length of lag, i, is set to be two and three, for the short leg and for the long leg, respectively, in order to be consistent with discovered predictability in each leg.

Then, the estimates for $\lambda_{Z,2}{}'s$ and $\lambda_{Z,3}{}'s$ are obtained by forecasting the OECD industrial production growth in month t (ΔIP_t^{OECD}) using each of the eight predictors in month $t-2$ and in month $t-3$, respectively.

The first plot in the figure, Short leg: ΔIP_t^{OECD}, presents a scatter plot of the coefficients $\lambda_{Z,2}{}'s$ on the coefficients $\beta_{Z,2}^{3short}{}'s$. The second plot in the figure, Long leg: ΔIP_t^{OECD}, presents a scatter plot of the coefficients $\lambda_{Z,3}{}'s$ on the coefficients $\beta_{Z,3}^{3long}{}'s$

In order to make slope estimates on different predictors comparable, all variables are normalized before estimating $\beta_{Z,i}^{K_l}{}'s$ and $\lambda_{Z,i}{}'s$ used in this figure.

Short leg: ΔIP_t^{OECD} Long leg: ΔIP_t^{OECD}



8. Predictability exists in currency components but not interest components

Is the predictability in carry trades a result of predictability in the exchange rate movement, or in the interest rate differential variations? Does the information contained in the predictors diffuse to exchange rates, or to interest differentials? Using the regressions specified in Equation (3) to test the predictability in the currency and interest component of carry trade profits, I find that the slope estimates on predictors for the currency components (Appendix 3.C) are almost identical to those in the carry trade profits reported in Table 3.3. As for the interest component in carry trade profits, after controlling for the lagged interest component, there is limited evidence of its predictability (Appendix 3.D). While the slope estimates on r_{t-3}^{world} for short-leg profits are statistically significant, the sizes of the coefficients are close to zero. Other significant results include the slope estimates of $\Delta\sigma_{t-2}^{FX}$ and $\Delta\sigma_{t-3}^{FX}$ for long-leg profits in month t, which have similar sizes but opposite signs at different lags. These findings imply that the information contained in the world equity return, changes in commodity prices and changes in equity volatility affect future exchange rates rather than future interest rates, as implied by the spot and forward rates.

9. Other predictors for carry trade profits

In the existing literature, many other variables have been considered as predictors for currency returns and carry trades by other studies. Do these variables also predict the short and long legs of dynamic carry trade profits? The following additional predictors for carry trades are considered: (1) Change in the CBOE VIX index, as in Brunnermeier, Nagel and Pedersen (2008), denoted by ΔVIX_t; (2) change in global liquidity, denoted by Δliq_t , based on Brunnermeier, Nagel and Pedersen (2008) and Bakshi and Panayotov (2012); (3) the term premium, denoted by $term_t$, based on Ang and Chen (2010); (4) average forward discount, denoted by AFD_t , based on Lustig, Roussanov, Verdelhan and Sloan (2012); and (5) percentage change in industrial production of the OECD countries, denoted by ΔIP_t^{OECD}, as a proxy for global economic growth, based on Lustig, Roussanov, Verdelhan and Sloan (2012). Appendix 3.B includes a detailed description of the construction of these predictors and the summary statistics.

First, I examine the in-sample significance of each of these additional predictors through the univariate predictive regressions specified in Equation (3). On the short leg, ΔVIX_t is found to significantly predict carry trade profits from all three strategies two months later (all p-values are below 0.05). AFD_t also significantly predicts short-leg profits for strategies 2 and 3 in the following month, with p-values of 0.06 and 0.08, respectively. On the long leg, $term_t$ significantly predicts profits from all three strategies in each of the three following months. No other variables show up as significant predictors for any strategy in any of the following three months.

Then, I test the marginal significance of these significant predictors by including important predictors studied in this paper, one at a time. The predictive ability of ΔVIX_t for short-leg carry trade profits in two months' time becomes insignificant in the presence of r_t^{world} and $\Delta\sigma_t^{equity}$. This result is driven by the high correlation between ΔVIX_t and r_t^{world} (-0.60) and between ΔVIX_t and $\Delta\sigma_t^{FX}$ (0.63). On the long leg,r_t^{CRB}, or commodity price changes, subsumes the predictive ability of $term_t$ for carry trade profits.

The test results suggest that there is limited evidence for in-sample predictive ability in other known predictors.[20] Neither do other known variables demonstrate comparable out-of-sample predictive ability, as demonstrated in their low out-of-sample R^2 and high MSPE-adjusted one-sided p-values (Appendix 3.J.).

10. Time-varying risk premia?

While the evidence so far points towards a delayed reaction explanation, return predictability is not necessarily a result of market inefficiency. Return predictability can be an effect of time-varying risk-premia. For example, Fama and French (1989) show that many well-known predictors for stock returns, such as dividend yield, term structure and the default premium, serve as proxies for business risks. Business risks are high during economic downturns – thus, investors expect high returns to

[20] Results for other predictors are included in Appendix 3.I.

compensate for increased business risks. Carry trade profits, like stock returns, also display cyclical natures (for example, Lustig, Roussanov, Verdelhan and Sloan, 2012). Hence, it is necessary to verify whether the observed predictability is a result of time-varying risk premia. While Bakshi and Panayotov (2012) obtain mixed evidence related to risk explanation using a latent variable model and a test developed by Kirby (1998), this paper tries to provide additional evidence in this regard by investigating four additional areas, which are predictability at longer horizons, correlation with economic variables, consistency with predictions from equilibrium theory and predictable negative profits.

10.1.1. Predictability at longer horizons

The predictability associated with time-varying risk premia tends to strengthen at longer horizons (Cochrane, 2005). The analogous question is whether observed predictability in carry trades survives at long horizons. This section tests the long-run predictability using regressions specified as follows:

$$\overline{P}_t^{k_l} = \alpha + \beta_i \ Z_{t-i} + \gamma \overline{P}_{t-1}^{k_l} + \mu_t$$

$$(i = 1 \cdots 6, k = 1 \cdots 3, \ l = short, long, long/short) \,, \qquad (7)$$

where $\overline{P}_t^{k_l}$ is the short-leg profit, long-leg profit and long/short profit from each of the three strategies (nine profits in total), and Z_{t-i} is a single predictor in each of the six previous months. Estimation results are reported in Table 3.6.

Contrary to the predictability associated with time-varying risk premia, the results in Table 3.6 suggest that the predictability in carry trades using r_{t-i}^{world}, $\Delta\sigma_{t-i}^{equity}$, $\Delta\sigma_{t-i}^{FX}$ and r_{t-i}^{CRB} is a short-run phenomenon. The predictability effect for the short-leg carry trade disappears if one considers the world equity index return and equity volatility changes lagged more than two months. Increases (decreases) in average currency volatility significantly predict decreases (increases) in short-leg carry trade profits two and four months later, but the effect is partially reversed in the fifth month. On the long leg, the predictive ability of $\Delta\sigma_t^{equity}$, $\Delta\sigma_t^{FX}$ and r_t^{CRB} all weaken

Table 3.6 Predictability in carry trade profits at longer horizons

This table reports coefficient estimates from regressions $\overline{P}_t^{k_l} = \alpha + \beta_i\ Z_{t-i} + \gamma \overline{P}_{t-1}^{k_l} + \mu_t$ $(i = 1 \cdots 6, k = 1 \cdots 3,\ l = short, long, long/short)$, where $\overline{P}_t^{K_l}$ denotes the profits from betting one U.S. dollar on K low-yielding currencies ($\overline{P}_t^{K_{short}}$), the profits from betting one U.S. dollar on K high-yielding currencies ($\overline{P}_t^{K_{long}}$), and the profits from betting half a U.S. dollar on each leg ($\overline{P}_t^{K_{long/short}}$) and Z_{t-i} is a predicting variable.

The individual predictors for the short-leg carry trade profits are the MSCI World Equity Price Index return (r_{t-i}^{world}), changes in equity volatility ($\Delta\sigma_{t-i}^{equity}$) and changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$). The individual predictors for the long-leg carry trade profits and long/short carry trade profits are percentage changes in commodity prices (r_{t-i}^{CRB}), changes in equity volatility ($\Delta\sigma_{t-i}^{equity}$) and changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$).

The estimates for the predictive coefficient β_i are reported with two-sided heteroskedasticity consistent p-values. p-values lower than 0.10 are denoted in bold font. The sample period runs from January 1985 to December 2011.

Month	Strategy K	$t-1$ $\boldsymbol{\beta_1}$	p	$t-2$ $\boldsymbol{\beta_2}$	p	$t-3$ $\boldsymbol{\beta_3}$	p	$t-4$ $\boldsymbol{\beta_4}$	p	$t-5$ $\boldsymbol{\beta_5}$	p	$t-6$ $\boldsymbol{\beta_6}$	p
Predictors for short-leg profits													
chg. in equity volatility,	1	0.05	0.94	-1.61	<0.01	0.48	0.41	-0.02	0.94	0.00	0.99	-0.17	0.60
$\Delta\sigma_t^{equity}$	2	0.29	0.57	-1.44	<0.01	0.62	0.19	0.04	0.89	0.01	0.96	-0.17	0.54
	3	0.27	0.60	-1.49	<0.01	0.62	0.20	0.04	0.89	0.03	0.93	-0.18	0.50
chg. in currency	1	0.98	0.49	-3.84	0.02	0.76	0.62	-2.44	0.07	2.12	0.06	-0.03	0.97
volatility, $\Delta\sigma_t^{FX}$	2	1.22	0.24	-2.74	0.03	1.08	0.35	-2.34	0.02	1.75	0.06	-0.37	0.60
	3	0.96	0.35	-2.55	0.04	1.12	0.33	-2.29	0.02	1.61	0.07	-0.24	0.72
world equity	1	0.07	0.11	0.12	0.03	0.00	0.95	0.00	0.96	0.00	0.89	0.02	0.55
index return,	2	0.04	0.21	0.10	0.02	-0.02	0.55	-0.01	0.73	0.01	0.81	0.01	0.69
r_t^{world}	3	0.04	0.26	0.10	0.02	-0.03	0.49	-0.02	0.61	0.00	0.86	0.01	0.75

Month		$t-1$		$t-2$		$t-3$		$t-4$		$t-5$		$t-6$	
	Strategy K	$\boldsymbol{\beta_1}$	p	$\boldsymbol{\beta_2}$	p	$\boldsymbol{\beta_3}$	p	$\boldsymbol{\beta_4}$	p	$\boldsymbol{\beta_5}$	p	$\boldsymbol{\beta_6}$	p
Predictors for long-leg profits													
chg. in CRB	1	0.13	0.09	0.05	0.64	0.30	<0.01	0.15	0.07	0.00	0.98	-0.15	0.03
index, r_t^{CRB}	2	0.13	0.06	0.06	0.44	0.26	<0.01	0.12	0.15	-0.05	0.66	-0.14	0.04
	3	0.12	0.07	0.05	0.56	0.21	<0.01	0.09	0.18	0.00	0.97	-0.12	0.04
chg. in equity volatility,	1	-0.35	0.56	0.75	0.10	-1.11	0.04	-0.35	0.50	-0.36	0.40	0.11	0.82
$\Delta\sigma_t^{equity}$	2	-0.22	0.73	0.50	0.21	-1.03	0.02	-0.40	0.40	0.16	0.72	0.12	0.79
	3	-0.27	0.67	0.57	0.11	-0.92	0.02	-0.25	0.51	0.02	0.95	0.15	0.71
chg. in currency	1	-1.42	0.40	-0.87	0.65	-3.00	0.10	0.29	0.86	-0.27	0.85	0.43	0.78
volatility, $\Delta\sigma_t^{FX}$	2	-1.63	0.25	-0.19	0.90	-2.95	0.06	-0.32	0.83	0.48	0.75	0.08	0.95
	3	-1.65	0.24	-0.01	0.99	-2.25	0.08	0.14	0.91	-0.01	0.99	0.27	0.82
Predictors for short/long strategy profits													
chg. in CRB	1	0.13	0.04	0.15	0.01	0.21	0.01	0.12	0.09	-0.05	0.55	-0.16	<0.01
index, r_t^{CRB}	2	0.12	0.02	0.12	0.02	0.17	0.02	0.08	0.23	-0.08	0.35	-0.14	0.01
	3	0.11	0.03	0.10	0.03	0.13	0.01	0.06	0.25	-0.06	0.46	-0.13	0.01
chg. in equity volatility,	1	-0.16	0.74	-0.31	0.50	-0.78	0.16	-0.38	0.41	-0.16	0.68	-0.08	0.86
$\Delta\sigma_t^{equity}$	2	-0.05	0.89	-0.34	0.39	-0.70	0.17	-0.39	0.35	0.23	0.59	-0.16	0.70
	3	-0.12	0.75	-0.37	0.28	-0.55	0.21	-0.26	0.43	0.13	0.71	-0.15	0.68
chg. in currency	1	-0.20	0.89	-2.72	0.10	-2.87	0.07	-1.31	0.38	1.33	0.29	-0.05	0.97
volatility, $\Delta\sigma_t^{FX}$	2	-0.78	0.52	-1.61	0.26	-2.36	0.08	-1.97	0.15	1.79	0.18	-0.37	0.77
	3	-0.88	0.43	-1.56	0.17	-1.64	0.13	-1.54	0.18	1.39	0.22	-0.26	0.81

drastically after three months. These results suggest that predictability is short-lived and that the world equity index return (r_t^{world}), average equity volatility changes ($\Delta\sigma_t^{equity}$), average currency volatility changes ($\Delta\sigma_t^{FX}$) and commodity price changes (r_t^{CRB}) do not serve as an indication of time-varying risk premia.

10.1.2. Correlation with economic variables

Lustig et al. (2012) show that the average forward premium (or average interest rate differential) and industrial production growth capture the business cycle risk and predict U.S. dollar carry trades. The predictive ability of the average forward premium and industrial production growth for the U.S. dollar carry trades are particularly strong at long horizons. If the average foreign interest rate is above the U.S. interest rate and industrial production drops in the U.S., the U.S. dollar tends to depreciate against foreign currencies on average in the next year. Based on Lustig et al. (2012), this paper considers the correlation between industrial production growth in the OECD countries[21] and carry trade predictors, and between the average forward premium and carry trade predictors (results shown in Panel B of Appendix 3.A). The maximum correlation is between the commodity price change movement and the industrial production growth (0.30). Other correlations vary between -0.02 and 0.08. These low correlations suggest that the world equity index return, the commodity price movement, changes in equity volatility and changes in currency volatility do not proxy for time-varying risks across business cycles. Earlier in this paper, the main predictive results are shown to be robust to the OECD industrial production growth and the average forward premium.

[21] Lustig et al. (2012) employ a dollar carry trade strategy where investors are exposed to the U.S. economic risk. Carry trades in this study are dollar neutral, so their investors are exposed to the global risk. Thus, the predicting variable is industrial production growth in the OECD countries instead of the U.S. industrial production growth.

10.1.3. Equilibrium theory

Equilibrium theory suggests that the predictability discussed in this paper is not related to a risk premium. According to the equilibrium theory, some variables proxy for business risk across economic cycles and higher risk should predict higher returns. Take the equity index return as an example: if a negative world equity index return predicts carry trade profits as a result of risk, the equilibrium theory suggests that drops in world equity prices, which indicate higher risks, should lead to higher average profits from carry trades. This study finds, however, that a drop in world equity prices leads to decreases in carry trade profits. Similarly, increases in average equity volatility and average currency volatility are related to increases in risk. If these variables are proxies for business risk across the economic cycle, then increases in volatility should predict higher carry trade profits. This inference also is inconsistent with findings in this study, where increases in volatility predict lower future profits. In the context of currency carry trades, drops in commodity prices are generally considered to be bad news for commodity currencies, because they negatively affect the term of trades in these commodity exporting countries. If one assumes commodity price changes to be a proxy for business risk, the results in this study suggest that increased risk predicts lower returns, which is inconsistent with the risk premia explanation.

10.1.4. Negative carry trade profits

Finally, following Eleswarapu and Thompson (2007) and Driesprong, Jacobsen and Maat (2008), this section implements a negative excess return test based on a suggestion by Schwert (2003), in order to obtain more conclusive evidence. Schwert (2003) suggests that, in the case of market inefficiency, the predicted excess return should frequently be negative. Driesprong, Jacobsen and Maat (2008, p. 308) refer to this standard as an “extreme standard”, because it does not consider risk. Economic variables such as dividend yield and default premium fail this negative excess return test. For instance, Eleswarapu and Thompson (2007) find that during the period from 1951 to 2000, the term premium is the variable that predicted the highest number of negative excess returns. The term premium predicted negative excess returns for 11%

of all months. The dividend yield predicted 3% of months as having negative risk premia during the same period, while the default premium predicted none.

The analogous question in this study is whether the world equity index return, changes in equity volatility, changes in currency volatility and changes in commodity prices frequently predict negative carry trade profits.[22] If the predictor variables are proxies for risk, they should not predict many negative carry trade profits.

First, in-sample predictions are generated as a proxy for expected negative profits from the following equation:

$$\overline{P}_t^{k_{short}} = \alpha + \beta_1^{short} Z_{t-2} + \mu_t^{short} , \overline{P}_t^{k_{long}} = \alpha + \beta_1^{long} Z_{t-3} + \mu_t^{long},$$

$$\overline{P}_t^{k_{long/short}} = \alpha + \beta_1^{long/short} Z_{t-3} + \mu_t^{long/short} \qquad (k = 1 \cdots 3), \quad (8)$$

where Z_{t-i} is a single predictor in month $t - i$ for profits from the short-leg, the long-leg and the long/short profit, and $\overline{P}_t^{K_{short}}$ ($\overline{P}_t^{K_{long}}$ and $\overline{P}_t^{K_{short/long}}$) is the monthly profit from the short-leg, the long-leg and long/short profits using K currencies on each leg. Then, the percentage of negative expected profits is computed. If the predictability effect is the result of a delayed reaction, negative predicted carry trade profits should occur in a high percentage of months. Taking a different perspective, if the predictability is a result of market in-efficiency, then a one standard deviation change in an independent variable around its mean should be able to predict negative profits. The minimum standard deviation is computed from the fitted predictive equations and the mean and standard deviation of predictors.

The results are presented in Table 3.7 and indicate that r_{t-2}^{world} and r_{t-3}^{CRB} predict negative profits in many months. The world equity index return in month $t - 2$ frequently predicts negative short-leg profits in month t, in as many as 42% to 46%

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[22] As carry trades involve borrowing in low-yielding currencies, the profits should be compared to excess stock returns.

of months, for all three strategies. For the long leg of (long/short) carry trades, the percentage of months with negative profits predicted by r_{t-3}^{CRB} range between 19% (19%) to 24% (20%) for the three strategies. While $\Delta\sigma_{t-2}^{equity}$ and $\Delta\sigma_{t-2}^{FX}$ predict negative profits from shorting low-yielding currencies in month t almost half of the time (43% to 49%), $\Delta\sigma_{t-3}^{equity}$ and $\Delta\sigma_{t-3}^{FX}$ predict negative long-leg (long/short) profits in as few as 5% to 11% (7% to 12%) of months. Further, approximately more than half a standard deviation drop in r_{t-3}^{CRB} would predict negative carry trade profits in month t, from the long-leg and long/short strategy. For $\Delta\sigma_{t-3}^{FX}$ and $\Delta\sigma_{t-3}^{equity}$, the increase needs to be more than one standard deviation in order to predict negative profits from the long-leg and the long/short strategies in month t. By contrast, in order to predict negative expected profits on the short leg,r_{t-2}^{world}, $\Delta\sigma_{t-2}^{FX}$ and $\Delta\sigma_{t-2}^{equity}$ do not need to move at all, or only need to move a little (the maximum change required is 0.08 standard deviations). This can be primarily a result of the negative realized average profits on the short leg. The evidence is mixed in regards to whether changes in currency volatility and changes in equity volatility proxy for time-varying risk factors. Based on the results from these tests, however, one can reject the hypothesis that the predictive effect in carry trades from lagged world equity index changes and commodity price movements is a consequence of time-varying risk premia.

Table 3.7 Predicting negative carry trade profits

This table reports the percentage of negative expected profits and the number of standard deviations away from mean required for predictors to predict expected negative profits. In-sample predictions for carry trade profits are generated using the regression:

$$\overline{P}_t^{K_{short}} = \alpha + \beta_{Z,2}^{K_{short}} Z_{t-2} + \mu_t^{short}, \overline{P}_t^{K_{long}} = \alpha + \beta_{Z,3}^{K_{long}} Z_{t-3} + \mu_t^{long},$$

$$\overline{P}_t^{K_{long/short}} = \alpha + \beta_{Z,3}^{K_{long/short}} Z_{t-3} + \mu_t^{long/short} \qquad (K = 1 \cdots 3), \quad (8)$$

where $\overline{P}_t^{k_{short}}$ denotes the profits from betting one U.S. dollar on K lowest-yielding currencies, $\overline{P}_t^{k_{long}}$ denotes the profits from betting one U.S. dollar on K highest-yielding currencies, $\overline{P}_t^{k_{long/short}}$ denotes the profits from betting half a U.S. dollar on each leg and Z_{t-i} is a single predictor in month $t-i$.
The column "% of negative expected profits" reports the percentage of months with negative predicted profits. The column "min. standard deviation from mean" reports the minimum number of standard deviations away from the mean that a predictor needs to be in order to generate negative carry trade profits. The minimum standard deviation is computed from fitted predictive equations and the mean and standard deviation of the predictors.

	Strategy	% of negative expected profits	min. standard deviation from mean
Predictors for short-leg profits			
chg. in equity	K=1	46%	0.00
volatility, $\Delta\sigma_{t-2}^{equity}$	K=2	40%	0.05
	K=3	42%	0.03
chg. in currency	K=1	49%	0.00
volatility, $\Delta\sigma_{t-2}^{FX}$	K=2	44%	0.09
	K=3	46%	0.06
world equity	K=1	47%	0.00
index return,	K=2	43%	-0.05
$\boldsymbol{r_{t-2}^{world}}$	K=3	43%	-0.02
Predictors for long-leg profits			
chg. in CRB	K=1	19%	-0.71
index, r_{t-3}^{CRB}	K=2	21%	-0.64
	K=3	24%	-0.58
chg. in equity volatility,	K=1	5%	1.30
$\Delta\sigma_{t-3}^{equity}$	K=2	7%	1.14
	K=3	8%	0.94
chg. in currency	K=1	8%	1.31
volatility, $\Delta\sigma_{t-3}^{FX}$	K=2	10%	1.09
	K=3	11%	1.02
Predictors for short/long strategy profits			

	Strategy	% of negative expected profits	min. standard deviation from mean
chg. in CRB index, r_{t-3}^{CRB}	K=1	20%	-0.66
	K=2	19%	-0.71
	K=3	19%	-0.69
chg. in equity volatility, $\Delta\sigma_{t-3}^{equity}$	K=1	7%	1.18
	K=2	7%	1.14
	K=3	8%	1.04
chg. in currency volatility, $\Delta\sigma_{t-3}^{FX}$	K=1	14%	0.90
	K=2	12%	0.98
	K=3	12%	0.99

11. Conclusion

The main contribution of this paper is that it is the first study to document evidence for the predictability in the short-leg of dynamic carry trades and low-yielding currencies. Following drops in the world equity index levels, rises in equity volatility and rises in currency volatility, profits from shorting low-yielding currencies tend to decrease. Further, the predictability in the short leg is of significant economic value to carry trade investors. By predicting profits and making trade decisions for each leg separately, an investor can improve the combined long/short carry trade profit, its Sharpe-ratio and its skewness, relative to when they stay fully invested in carry trades and relative to when they rely on a single prediction model for profits from both legs. It seems unlikely that this predictability can be attributed to time-varying risk premia, because the predictability is short-lived and inconsistent with the predictions from the equilibrium theory, where increased uncertainty is associated with higher expected returns. If predictors including the world equity index return (changes in equity volatility, changes in currency volatility and changes in commodity prices) indeed serve as proxies for business cycle risk, drops in world equity prices (increase in equity volatility, increase in currency volatility and decreases in commodity prices) should lead to higher carry trade profits, not lower profits as found in this study.

A possible explanation for the findings in this study is that carry trade investors react at different points in time to changes in equity prices, changes in commodity prices, changes in equity volatility and changes in currency volatility, or carry trade investors may have difficulty in assessing the impact of these changes on exchange rates. Results in this study appear to be more consistent with the gradual information diffusion hypothesis put forward by Hong and Stein (1999) and Hong, Torous and Valkanov (2007). First, the results are strongest in two to three months' time. As a lag of one to 12 weeks is introduced between carry trade profits and the predictors, the explanatory power of predictive regressions increases, peaks and then quickly drops. This pattern is in line with the delayed reaction of investors. Second, the ability of a variable to predict carry trade profits correlates strongly with its ability to forecast economic fundamentals, as proxied for by industrial production growth in the OECD countries. This strong positive correlation suggests that these predicting variables (changes in commodity prices, the world equity index return, changes in equity volatility and changes in currency volatility) may contain information related to economic fundamentals, which gradually flows through asset markets.

Chapter 4 Cross-asset Return Predictability: Carry Trades, Stocks and Commodities[1]

Abstract

In a dynamic setting defined by vector autoregressive models, predictive effects go from commodities to carry trades that long high-yielding currencies, from commodities to stocks and from stocks to carry trades that short low-yielding currencies. Contemporaneously, these variables are more correlated for the downside movements than for the upside movements. Many of the predictive effects are also asymmetric: drops, but not rises, in the world equity index (commodity prices) predict carry trade decreases in profits from the short leg (the long leg); increases, but not decreases in currency volatility predict rises in carry trade profits from the short leg. In contrast, the predictive effects from changes in equity volatility to carry trade profits are symmetric. Prediction models utilizing these asymmetric effects do not deliver more accurate out-of-sample forecasting than symmetric models defined in the last chapter.

JEL classifications: G11, G14, F31

Keywords: Carry Trade; Return Predictability; Gradual Information Diffusion; Safe-haven Currencies; Information and Market Efficiency; Asymmetric Correlations; Vector Autoregression

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[1] This chapter is a paper I co-authored with Professor Ben Jacobsen.

1. Introduction

In the last chapter, I showed that carry trade profits from the high-yielding currencies and those from the long-yielding currencies are predicted by different economic variables. Results in Chapter 3 suggest that predictive effects go from commodities to currencies and from stocks to currencies. It is possible that the predictive effect also goes the other way around, from currencies to stocks and from commodities to currencies. For example, Chen, Rogoff and Rossi (2010) find that commodity currencies predict commodity prices. Granger, Huangb and Yang (2000) show that, during the 1997 Asian financial crisis, currencies led stocks in some countries but in other countries it was just the opposite. This chapter investigates the cross-asset return predictability among three types of assets, namely, the carry trades, the MSCI world equity portfolio and the CRB Raw Industrial Commodity Index. Using vector autoregressive models, I find that the predictive effects are from commodities to high-yielding currencies, from commodities to the world equity index and from the world equity index to low-yielding currencies. Plots of impulse-response functions suggest that carry trade profits from the short leg respond to a shock to the world equity index with a delayed temporary effect. Similarly, the response in long-leg carry trade profits to a shock to commodity prices is also temporary and with a delay. This pattern appears to be consistent with an under-reaction story.

Motivated by the anecdotal observation that a “bad” market and a “good” market may affect low- and high-yielding currencies differently, I further test the asymmetric effects in carry trade predictability. Contemporaneously, drops in the world equity index, decreases in commodity prices and carry trade losses are more correlated than their upside movements. Correlations between drops in prices in these three assets and increases in either equity volatility or currency volatility are also higher than those between increase in prices and drops in volatility. Turning to the asymmetric prediction, in-sample, I find an asymmetric effect from the world equity index return on short-leg carry trade profits and from commodity prices on long-leg carry trade profits. Drops, but not rises, in the world equity index return two months ago predict decreases in carry trade profits from low-yielding currencies in this month. Similarly, decreases but not increases in commodity prices three months before significantly predict drops in carry trade profits from high-yielding currencies in this month.

Changes in currency volatility also exhibit asymmetric effects on future profits from the short leg of carry trades – only increases in currency volatility significantly predict drops in the short-leg profits in two months' time.

In-sample, the asymmetric predictability is of economic significance. A one standard deviation monthly drop in the world equity index predicts an approximately 1.2 standard deviation decrease in the short-leg carry trade profits two months later. Similarly, a one standard deviation increase in currency volatility in a month tends to be followed by a one standard deviation decrease in carry trade profits from shorting the low-yielding currencies in two months' time. Sizes of these predictive coefficients in the high-risk regime almost double those estimates from the symmetric models in the previous chapter.

In contrast, changes in equity volatility do not demonstrate asymmetric effects on future carry trade profits. Rises and drops in equity volatility do not have significantly different slope estimates when they are used to predict carry trade profits. Decreases in commodity prices predict profits from high-yielding currencies more strongly than increases in commodity prices do, but the difference between slope estimates is only marginally significant.

Does the discussed asymmetric predictability persist over time? Rolling-window analysis shows that the slope estimates for drops in world index levels, rises in currency volatility and increases in commodity prices are stable over the sample period.

Would prediction models assuming asymmetry in predictability deliver better forecasting than simply using historical means as forecasts? Similar to the symmetric prediction models discussed in Chapter 3, these asymmetric models also deliver good out-of-sample performance, when I compare the $OoS\ R^{2\prime}s$ (Goyal and Welch, 2008) and MSPE one-tail-adjusted p-values (Clark and West, 2007) against those from historical mean models. However, the asymmetric models do not consistently deliver better out-of-sample performance than the symmetric prediction models in Chapter 3.

This chapter contributes to the literature in two respects. First, it relates to the predictability literature. Researchers have uncovered overwhelming evidence for short-run predictability in stock returns, in commodity prices and in carry trade profits. Existing studies either focus on volatility spill-over among markets or high-frequency dynamics, or use variables in one market to predict returns in another markets. By investigating return predictability among three major asset markets in a dynamic vector autoregression (VAR) setting, this essay reveals that predictability goes from commodity markets to equity markets and then low-yielding currencies and from commodities to high-yielding currencies; high-yielding currencies appear to predict stocks, but this effect is subsumed by commodity price changes. This study expands the knowledge on dynamic predictive relations among the three major asset markets.

Second, this chapter relates to the exchange rate forecast literature. To date, models that use macro-economic variables to predict exchange rates have had little success for horizons shorter than a year (for example, Meese and Rogoff, 1983; Mark, 1995; Cheung, Chinn and Pascual, 2005). There is some recent success in predicting exchange rates using currency order flow data (for example, Evans and Lyons, 2005). The mechanism through which order flows forecast exchange rates is analogous to the gradual information diffusion model by Hong and Stein (1999) and Hong, Torous and Valkanov (2007). Evans and Lyons (2005, 2007) explain that order flows forecast exchange rates by way of gradually dispersing information across the currency market. It is not only order flows in the currency market that forecast exchange rates. Albuquerque, Francisco and Marques (2008) document that stock market order flows also significantly explain future exchange rate movements. I contribute to this strand of literature by showing that stock returns and changes in equity volatility forecast returns of low-yielding currencies.

2. Data

This section briefly introduces variables used to investigate the cross-asset return predictability among commodities, currency and stocks. Motivation of choices of variables and details on how these variables are constructed can be found in Chapter 3.

Returns from currency investments are defined as dynamic carry trade profits from the short leg ($P_t^{K_{short}}, K = 1,2,3$) and profits from the long leg ($P_t^{K_{long}}, K = 1,2,3$), which were introduced in Chapter 3. Changes in currency volatility ($\Delta\sigma_t^{FX}$) are used as a proxy for the currency market risks.

Risks in the global equity markets are defined as monthly changes in the average equity volatility, denoted as $\Delta\sigma_t^{equity}$. In addition to monthly changes in average global equity volatility, I also consider monthly percentage changes in the MSCI World Equity Price Index as a predictor for carry trades.[2] Stock return data cover the same sample period as the exchange rate data (1985:01 to 2011:12).

Following the previous chapter, this chapter uses monthly percentage changes in the Raw Industrial Spot Commodity Index, denoted as r_t^{CRB}, to investigate whether carry trade profits predict commodity price movements.

3. Symmetric predictability between currency and equity and between currency and commodity

Chapter 3 already showed that commodity price changes predict carry trade profits from the long leg and either the world equity index return or changes in equity volatility predict profits from the short leg. It is possible that the predictability also goes from currency markets to stock markets and from currency to commodity markets. For example, Chen and Rogoff (2002) document that commodity prices and commodity currencies tend to move together. High-yielding currencies in dynamic carry trades tend to be commodity currencies, including the Australian dollar, the New Zealand dollar and the Norwegian krone. If high-yielding currencies contain information of commodity prices, profits from investing in high-yielding currencies may predict stock returns. Another interesting study by Chen, Rogoff and Rossi (2010) shows commodity currencies predict commodity prices outside of periods with structural breaks. In Chapter 3, I demonstrate that variations in carry trade profits are

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[2] Instead of using the total return index, this study uses percentage changes in the MSCI World Equity Price Index to predict carry trade profits, because the price index is more commonly reported in the news and more readily available than the total return index.

primarily driven by movements in exchange rates. Thus, carry trade profits from the long leg contain information about commodity currencies which can be useful predictors for changes in commodity prices.

In this section, I first use simple OLS regressions to investigate whether this predictive relation can also go from currencies to stocks and from currencies to commodities. Then, I examine this cross-asset predictability in a more dynamic setting using VAR models.

First, I test whether currency market variables predict the world equity index return by running the follow regression:

$$rx_t^{world} = \alpha + \beta_i \; Z_{t-i} + \gamma rx_{t-1}^{world} + \mu_t \quad (i = 1 \cdots 3, K = 1 \cdots 3), \tag{1}$$

where rx_t^{world} is the MSCI World Index total return in excess of the risk-free rate[3]; and Z_{t-i} is a single predictor, which is either profits from each of the three short-leg strategies($\overline{P}_{t-i}^{1short}, \overline{P}_{t-i}^{2short}, \overline{P}_{t-i}^{3short}$), profits from each of the three long-leg strategies ($\overline{P}_{t-i}^{1long}, \overline{P}_{t-i}^{2long}, \overline{P}_{t-i}^{3long}$) or changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$, as described in Chapter 3) in each of the three previous months. $\overline{P}_t^{long_K}$ ($\overline{P}_t^{short_K}$) is the profit to a U.S. investor from buying (selling) K ($K = 1, 2, 3$) high-yielding (low-yielding) currencies forward at the end of month $t - 1$. Details of the carry trade strategies can be found in Chapter 3.

Estimation results for regressions specified as Equation (1) are reported in Table 4.1. Long-leg carry trade profits from all three strategies ($\overline{P}_{t-3}^{k_{long}}$) significantly positively predict excess equity returns (rx_t^{world}) three months later. The magnitude of the predictive coefficients is, however, of marginal economic significance. For example, the change of a one annualised standard deviation of $\overline{P}_{t-3}^{3_{long}}$, or profits from investing in the three highest-yielding currencies, is 9.98%. This can lead to an annualised change of 2.47% in the MSCI World Index total return (a 0.15 standard deviation). Turning from currency returns to

[3] The U.S. risk-free rates are sourced from Kenneth French's data library.

currency volatility: a change in currency volatility does not predict movements in the world equity index in any of the three following months.

Table 4.1 Predicting the excess world equity index return carry trade payoff in-sample

This table reports the coefficient estimates from the regression:

$$rx_t^{world} = \alpha + \beta_i \ Z_{t-i} + \gamma rx_{t-1}^{world} + \mu_t \ \ (i = 1 \cdots 3, K = 1 \cdots 3), \qquad (1)$$

where rx_t^{world} is the MSCI world index total return in excess of the risk-free rate, and Z_{t-i} is a single predictor.

The single predictor Z_{t-i} is either the carry trade profit ($\overline{P}_{t-i}^{k_{short}}$ or $\overline{P}_{t-i}^{k_{long}}$), or changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$), in each of the three previous months. $\overline{P}_t^{long_K}$ ($\overline{P}_t^{short_K}$) is the profit to a U.S. investor from buying (selling) K high-yielding (low-yielding) currencies forward at the end of month $t-1$. Details of the carry trade strategies can be found in Chapter 3. The U.S. risk-free rates are sourced from the Kenneth French's data library.

The estimates for predictive coefficient β_i are reported with two-sided heteroskedasticity consistent p-values and adjusted R^2 (shown as $\bar{R}^2$). p-values corresponding to a 10%, or better, significance level are bolded. The sample period runs from January 1985 to December 2011.

	month $t-1$			month $t-2$			month $t-3$		
Predictors	β_1	p	$\bar{R}^2$	β_2	p	$\bar{R}^2$	β_3	p	$\bar{R}^2$
$\overline{P}_{t-i}^{1short}$	0.06	0.53	0.2%	0.02	0.85	-0.1%	-0.08	0.44	0.1%
$\overline{P}_{t-i}^{2short}$	0.00	1.00	0.0%	0.05	0.63	0.0%	-0.08	0.46	0.0%
$\overline{P}_{t-i}^{3short}$	0.00	0.98	0.0%	0.04	0.73	-0.1%	-0.11	0.30	0.2%
$\overline{P}_{t-i}^{1long}$	0.04	0.67	0.1%	-0.17	0.11	1.5%	0.17	**0.07**	1.5%
$\overline{P}_{t-i}^{2long}$	0.07	0.56	0.2%	-0.10	0.46	0.3%	0.20	**0.06**	1.5%
$\overline{P}_{t-i}^{3long}$	0.11	0.40	0.3%	-0.11	0.47	0.3%	0.25	**0.04**	1.9%
$\Delta\sigma_{t-i}^{FX}$	-0.79	0.67	0.7%	-0.29	0.87	0.7%	-1.24	0.46	0.9%

Second, I test whether currency market variables predict changes in commodity prices by running the follow regression:

$$r_t^{CRB} = \alpha + \beta_i \ Z_{t-i} + \gamma r_{t-1}^{CRB} + \mu_t \ \ (i = 1 \cdots 3), \qquad (2)$$

where r_t^{CRB} is monthly percentage changes in the CRB Raw Industrial Commodity Spot Index and Z_{t-i} is a single predictor, which is profits from each of the three short-leg strategies ($\overline{P}_{t-i}^{1short}, \overline{P}_{t-i}^{2short}, \overline{P}_{t-i}^{3short}$), profits from each of the three long-leg strategies

($\overline{P}_{t-i}^{1long}, \overline{P}_{t-i}^{2long}, \overline{P}_{t-i}^{3long}$) or changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$) in each of the three previous months.

Table 4.2 Predicting changes in commodity prices in-sample

This table reports the coefficient estimates from the regression:

$$r_t^{CRB} = \alpha + \beta_i \; Z_{t-i} + \gamma r_{t-1}^{CRB} + \mu_t \quad (i = 1 \cdots 3), \qquad (2)$$

where r_t^{CRB} is monthly percentage changes in the CRB Raw Industrial Commodity Spot Index and Z_{t-i} is a single predictor.

The single predictor Z_{t-i} is either the carry trade profit ($\overline{P}_{t-i}^{k_{short}}$ or $\overline{P}_{t-i}^{k_{long}}$), or changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$), in each of the three previous months. $\overline{P}_t^{long_K}$ ($\overline{P}_t^{short_K}$) is the profit to a U.S. investor from buying (selling) K ($k = 1, 2, 3$) high-yielding (low-yielding) currencies forward at the end of month $t-1$. Details of the carry trade strategies can be found in Chapter 3.

The estimates for predictive coefficient β_i are reported with two-sided heteroskedasticity consistent p-values and adjusted R^2 (shown as $\bar{R}^2$). p-values corresponding to a 10%, or better, significance level are bolded. The sample period runs from January 1985 to December 2011.

	month $t-1$			month $t-2$			month $t-3$		
Predictors	β_1	p	$\bar{R}^2$	β_2	p	$\bar{R}^2$	β_3	p	$\bar{R}^2$
$\overline{P}_{t-i}^{1short}$	0.00	0.94	11.2%	0.01	0.76	11.3%	-0.06	0.15	11.8%
$\overline{P}_{t-i}^{2short}$	0.02	0.74	11.3%	0.02	0.75	11.3%	-0.10	**0.06**	12.2%
$\overline{P}_{t-i}^{3short}$	0.03	0.66	11.3%	0.01	0.85	11.3%	-0.11	**0.05**	12.4%
$\overline{P}_{t-i}^{1long}$	0.04	0.32	11.4%	0.04	0.38	11.5%	0.04	0.41	11.5%
$\overline{P}_{t-i}^{2long}$	0.08	0.14	11.9%	0.06	0.33	11.7%	0.04	0.39	11.6%
$\overline{P}_{t-i}^{3long}$	0.07	0.25	11.6%	0.06	0.38	11.7%	0.06	0.28	11.7%
$\Delta\sigma_{t-i}^{FX}$	-1.31	0.31	11.8%	-0.54	0.55	11.4%	-0.30	0.75	11.4%

Estimation results for regressions specified as Equation (2) are reported in Table 4.2. Short-leg carry trade profits from the two-currency strategy ($\overline{P}_{t-3}^{2short}$) and from the three-currency strategy ($\overline{P}_{t-3}^{3short}$) significantly negatively predict excess equity returns (rx_t^{world}) three months later, but the size of the coefficients is of little economic significance. The change of a one annualised standard deviation of profits from investing in the three lowest-yielding currencies, or 9.17% of annualized profits, can lead to an annualised change of -1.00% in the CRB Raw Commodity index (a 0.10 standard deviation). Neither do changes in currency volatility predict commodity price changes in any of the three following months.

Last, I investigate the cross-asset return predictability among commodities, world equities and carry trades in a dynamic setting use two VAR models, one for low-yielding currencies and the other for high-yielding currencies,[4] with three monthly lags. Table 4.3 reports the VAR estimation results and Granger Causality Test results. There are two interesting findings in Table 4.3. *First*, in these VAR systems, the predictive ability of changes in commodity prices (r_{t-i}^{CRB}) stands out, because it not only Granger-causes the world equity index return (with p-values of 0.01 and 0.04 in Panel A and B of Table 4.3, respectively) but also Granger-causes the long-leg, or high-yielding-currency, carry trade profits (with a p-value of 0.01). The $Wald$-statistics and corresponding p-value in Panel B of Table 4.3 show that the long-leg profits ($\overline{P}_{t-i}^{3long}$), however, do *not* Granger-cause the world equity index returns. This result suggests that, in the OLS settings, the long-leg carry trade profits predict the world equity index return because the long-leg carry trade profits contain information related to commodity price changes and thus the predictability is not robust to changes in commodity prices. *Second*, the world equity index return (r_t^{world}) still Granger-causes the short-leg carry trade profits ($\overline{P}_t^{3short}$) in this VAR system.

[4] A parameter test rejects inclusion of both short-leg profits and long-leg profits in a single VAR system. This result suggests that low-yielding and high-yielding currencies do not significantly affect each other.

Table 4.3 Estimates from vector autoregressive (VAR) models

Panel A in this table reports the coefficient estimates using a VAR model with three months of lags of short-leg carry trade profits ($\overline{P}_t^{3short}$), the world equity index return (r_t^{world}) and changes in commodity prices (r_t^{CRB}). Panel B in this table reports the coefficient estimates using a VAR model with three months of lags of long-leg carry trade profits ($\overline{P}_t^{3long}$), the world equity index return (r_t^{world}) and changes in commodity prices (r_t^{CRB}). The last two columns in each panel report the Wald statistics and p-values against the null that the predicting variable in month $t-1$, $t-2$ and $t-3$ do *not* jointly Granger-cause the dependent variable.

The estimates for slope coefficient are reported with two-sided p-values. p-values corresponding to a 10%, or better, significance level are bolded. The sample period runs from January 1985 to December 2011.

Panel A.

	month $t-1$		month $t-2$		month $t-3$		Granger causality test	
	Coef.	p	Coef.	p	Coef.	p	Wald (χ^2)	p
Predicting $\overline{P}_t^{3short}$								
$\overline{P}_{t-i}^{3short}$	0.03	0.59	0.10	**0.06**	0.02	0.76		
r_{t-i}^{world}	0.02	0.51	0.09	**0.01**	-0.04	0.24	9.74	**0.02**
r_{t-i}^{CRB}	-0.03	0.58	0.10	**0.10**	-0.10	**0.08**	4.62	0.20
Predicting r_t^{world}								
r_{t-i}^{world}	0.10	**0.08**	-0.06	0.33	0.04	0.54		
$\overline{P}_{t-i}^{3short}$	-0.03	0.72	-0.04	0.67	-0.05	0.62	0.61	0.90
r_{t-i}^{CRB}	0.16	**0.10**	-0.15	0.13	0.27	**<0.01**	11.39	**0.01**
Predicting r_t^{CRB}								
r_{t-i}^{CRB}	0.30	**<0.01**	0.01	0.84	0.06	0.32		
$\overline{P}_{t-i}^{3short}$	0.03	0.64	0.02	0.73	-0.10	**0.09**	3.12	0.37
r_{t-i}^{world}	0.07	**0.06**	0.02	0.55	0.02	0.52	4.54	0.21

Panel B.

	month $t-1$		month $t-2$		month $t-3$		Granger causality test	
	Coef.	p	Coef.	p	Coef.	p	Wald (χ^2)	p
Predicting $\overline{P}_t^{3long}$								
$\overline{P}_{t-i}^{3long}$	0.12	**0.06**	0.00	0.98	0.09	0.17		
r_{t-i}^{world}	-0.04	0.28	0.01	0.76	-0.05	0.22	2.52	0.47
r_{t-i}^{CRB}	0.08	0.18	-0.04	0.50	0.18	**<0.01**	3.00	**0.01**
Predicting r_t^{world}								
r_{t-i}^{world}	0.12	0.05	-0.05	0.41	0.01	0.86		
$\overline{P}_{t-i}^{3long}$	-0.06	0.53	-0.01	0.90	0.12	0.24	1.78	0.62
r_{t-i}^{CRB}	0.17	**0.09**	-0.15	0.15	0.24	**0.02**	13.24	**0.04**
Predicting r_t^{CRB}								
r_{t-i}^{CRB}	0.28	**<0.01**	-0.01	0.91	0.06	0.31		
$\overline{P}_{t-i}^{3long}$	0.04	0.52	0.05	0.44	0.01	0.82	1.24	0.74
r_{t-i}^{world}	0.06	0.13	0.01	0.73	0.03	0.36	3.44	0.33

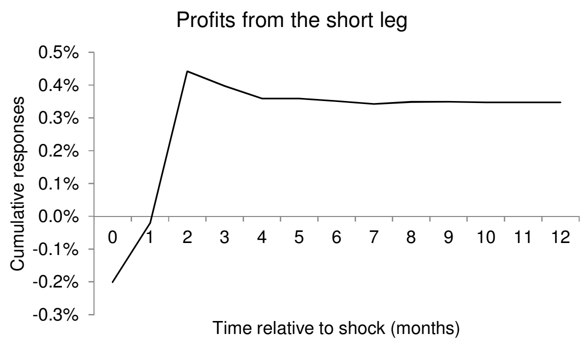
What would a one standard deviation shock in commodity price changes do to carry trade profits from high-yielding currencies and the world equity index return? How would a one standard deviation shock to the world equity index return affect carry trade profits from shorting the low-yielding currencies? In order to visualize these effects, I perform a Cholesky decomposition of the variance-covariance matrix of residuals with the changes in commodity prices first and then with the world equity index return, and consider a one standard deviation shock to commodity price changes and a one standard deviation shock to the world equity index return, respectively. The impulse-response plots are included in Figure 4.1. As the plot in Panel A of Figure 4.1 shows, the contemporaneous response in profits from shorting low-yielding currencies to drops in the world equity index is negative and becomes positive in the first month and second month. That is, short-leg carry trade profits first decrease contemporaneously as the world equity index rises and then also increases in the first and second month. Because the U.S. dollar depreciates against all currencies contemporaneously (shown in Appendix 4.A) when the world equity index rises, the initial reaction in low-yielding currencies to rises in the world equity index is that low-yielding currencies gain value against the U.S. dollar, resulting in a decrease in profits from shorting low-yielding currencies. In the following two months, low-yielding currencies gradually depreciate against the U.S. dollar, leading to increases in carry trade profits from the short leg. In contrast, the initial response in carry trade profits from high-yielding currencies is positive to a shock in commodity price changes (Panel B of Figure 4.1) – long-leg carry trade profits increase when commodity prices rise and the effect continues for about three months and then tapers off. The world equity index return also responds to commodity price changes with a similar pattern (Panel C of Figure 4.1). These patterns are consistent with a behavioural story of delayed investor reactions.

In summary, results in this section suggest that predictive effects go only one way from commodity markets to carry trades, from commodity markets to equity markets and from equity markets to carry trades, but not the other way around. Changes in commodity price predict both carry trade profits from longing high-yielding currencies and the world equity index return. Carry trade profits, from low-yielding currencies or from high-yielding currencies, do *not* predict commodity price changes. The world equity return predicts carry trade profits from shorting low-yielding currencies. At first sight, returns from investment in

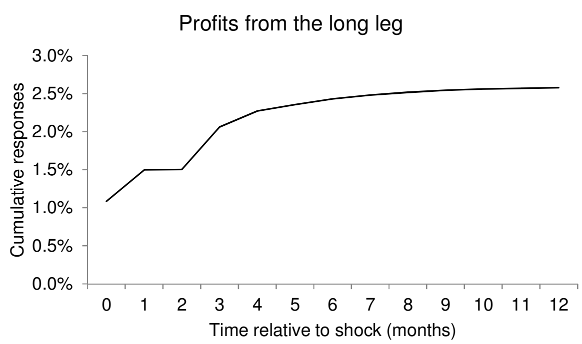
Figure 4.1 Impulse responses from a shock to stock returns and from a shock to commodity prices

The plot in Panel A is the monthly carry trade profits from the short leg ($\overline{P}_t^{3short}$) in response to a one standard deviation shock to the world equity index return (r_t^{world}). The impulse response in Panel A is based on an estimated vector autoregressive model that includes 20 monthly lags of changes in commodity prices (r_t^{CRB}), the world equity index return and carry trade profits from the short leg, with a Cholesky decomposition of the shock. The plot in Panel B is the monthly carry trade profits from the long leg ($\overline{P}_t^{3long}$) in response to a one standard deviation shock to the percentage changes in the commodity prices (r_t^{CRB}). The plot in Panel C is the monthly world equity index return (r_t^{world}) in response to a one standard deviation shock to the percentage changes in the commodity prices (r_t^{CRB}). The impulse response in Panel C is based on an estimated vector autoregressive model that includes 20 monthly lags of changes in commodity prices (r_t^{CRB}), the world equity index return and carry trade profits from the long leg, with a Cholesky decomposition of the shock.

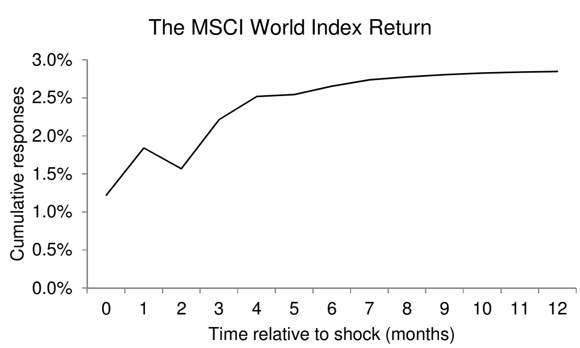
A



B



C



high-yielding currencies appear to predict the world equity index return, but such predictive ability is subsumed by changes in commodity prices. Impulse response plots display a pattern of delayed reactions in short-leg carry trade profits, after one month, to a shock in the world equity return and delayed reactions in long-leg carry trade profits, after two months, to a shock in changes in commodity prices. This pattern in impulse-response plots corroborates the findings in Chapter 3, which support an under-reaction behavioural story, instead of time-varying risk premia, as a most likely explanation for discovered predictability in carry trade profits.

4. Asymmetric predictability between carry trades and stocks and between carry trades and commodities

Contemporaneous correlations between asset returns are not necessarily symmetric. For example, Ang and Chen (2002) find that correlations between U.S. stocks and the aggregate U.S. market are much stronger for downside movements than for upside movements. Predictive effects from returns in one asset to returns in another asset can also be asymmetric. Lo and MacKinlay (1990) find that returns in large-firm stocks predict returns in small-firm stocks. Later, a study by McQueen, Pinegar and Thorley (1996) reveals that the cross-autocorrelations are associated with delayed reactions by small stocks to rises, but not drops, in prices of large stocks.

Do asset returns examined in this chapter also display asymmetry in correlations? If so, diversification benefits from carry trade investments, equity investments and commodity investments can differ in different states of the markets. Another related question is whether the discovered predictability in carry trade profits is asymmetric. If it is, then one might be better off using a prediction model that accounts for asymmetry. In the following subsections, I investigate the contemporaneous conditional correlations between these asset returns, test for the in-sample asymmetric predictability using OLS regressions and test for the out-of-sample asymmetric predictability and its economic significance.

4.1. Contemporaneous asymmetric correlations

Table 4.4 reports the pairwise correlations among all variables, conditional on high-risk regime and low-risk regime, respectively. High-risk regime correlations are pairwise correlations among negative world equity return, drops in commodity prices, negative term spreads, negative industrial production growth, increases in equity volatility, increases in currency volatility, increases in the VIX index and decreases in liquidity. Low-risk regime correlations are just the opposite.

When comparing estimates for correlation coefficients in Panel A with those in Panel B in Table 4.4, a few noticeable asymmetries stand out. *First*, drops in carry trade profits from the short leg are positively correlated with decreases in world equity index return, with correlation coefficients ranging between 0.19 and 0.41 (Panel A), while the correlation coefficients between increases in carry trade profits and rises in the world equity index are negative and ranging between -0.09 and -0.13 (Panel B). In contrast, correlations between carry trade profits from the long leg and the world equity index return are similar for both regimes – correlation coefficients range between 0.37 and 0.40 and between 0.31 and 0.34 for the high-risk regime and low-risk regime, respectively. *Second*, drops in commodity prices and carry trade losses from the long leg correlate more strongly than rises in commodity prices and carry trade gains from the long-leg carry trades – the high-risk regime correlations range between 0.39 and 0.51 (Panel A), while the low-risk regime correlations range between 0.17 and 0.22 (Panel B). Similarly, the high-risk regime correlation between changes in commodity prices and the world equity index return is 0.56, higher than the low-risk regime coefficient of 0.26. *Last*, in addition to the world equity index return and changes in commodity prices, other variables that predict carry trade profits also correlate more strongly with carry trade profits in the high-risk regime. For example, increases in equity volatility and carry trade losses from the long leg have correlation coefficients ranging between -0.41 and -0.51, but their counterparts in the low-risk regime are around zero.

Table 4.4 Asymmetric contemporaneous pairwise correlations between variables

This table reports pairwise correlations among all variables, conditional on high-risk regime (Panel A) and low-risk regime (Panel B). High- (low-) risk regime correlations are pairwise correlations among negative (positive) world equity return, drops (rises) in commodity prices, negative (positive) term spreads, negative (positive) industrial production growth, increases (decreases) in equity volatility, increases (decreases) in currency volatility, increases (decreases) in the VIX index and decreases (increases) in liquidity.

A. High-risk regime

	r_t^{world}	r_t^{CRB}	$term_t$	AFD_t	ΔIP_t^{OECD}	$\Delta\sigma_t^{equity}$	$\Delta\sigma_t^{fx}$	ΔVIX_t	Δliq_t
$\overline{P}_t^{1short}$	0.41	0.10	-0.26	-0.14	0.71	-0.16	-0.23	-0.17	-0.38
$\overline{P}_t^{2short}$	0.25	-0.23	-0.23	-0.02	0.66	-0.13	-0.24	-0.05	-0.29
$\overline{P}_t^{3short}$	0.19	-0.17	-0.20	-0.01	0.68	-0.11	-0.25	-0.10	-0.38
$\overline{P}_t^{1long}$	0.39	0.39	0.08	0.00	0.40	-0.51	-0.41	-0.45	-0.52
$\overline{P}_t^{2long}$	0.40	0.48	0.05	0.08	0.50	-0.41	-0.48	-0.33	-0.56
$\overline{P}_t^{3long}$	0.37	0.51	0.06	-0.01	0.38	-0.55	-0.55	-0.49	-0.47
r_t^{world}	1.00	0.56	-0.10	0.21	0.45	-0.72	-0.35	-0.72	-0.44
r_t^{CRB}		1.00	0.00	-0.02	0.39	-0.37	-0.53	-0.35	-0.45
$term_t$			1.00	-0.33	0.10	-0.21	-0.11	-0.08	-0.24
AFD_t				1.00	-0.05	-0.26	0.06	-0.20	-0.30
ΔIP_t^{OECD}					1.00	-0.57	-0.27	-0.39	-0.60
$\Delta\sigma_t^{equity}$						1.00	0.40	0.82	0.20
$\Delta\sigma_t^{fx}$							1.00	0.45	0.46
ΔVIX_t								1.00	0.32
Δliq_t									1.00

B. Low-risk regime

	r_t^{world}	r_t^{CRB}	$term_t$	AFD_t	ΔIP_t^{OECD}	$\Delta\sigma_t^{equity}$	$\Delta\sigma_t^{fx}$	ΔVIX_t	Δliq_t
$\overline{P}_t^{1short}$	-0.09	-0.10	-0.09	0.06	0.02	0.00	-0.06	0.04	-0.10
$\overline{P}_t^{2short}$	-0.13	-0.02	-0.08	-0.06	-0.02	0.04	-0.12	0.19	-0.30
$\overline{P}_t^{3short}$	-0.11	-0.05	-0.04	-0.04	0.04	0.07	-0.05	0.18	-0.29
$\overline{P}_t^{1long}$	0.31	0.22	-0.03	0.17	0.01	0.01	-0.09	-0.21	-0.12
$\overline{P}_t^{2long}$	0.34	0.17	-0.02	0.07	0.04	-0.07	0.00	-0.22	-0.18
$\overline{P}_t^{3long}$	0.34	0.18	-0.06	0.05	0.03	-0.08	-0.08	-0.30	-0.16
r_t^{world}	1.00	0.26	0.00	-0.01	0.01	-0.14	-0.20	-0.43	-0.05
r_t^{CRB}		1.00	0.22	-0.13	0.15	-0.12	-0.17	-0.23	-0.08
$term_t$			1.00	-0.48	0.15	0.16	-0.02	-0.01	0.27
AFD_t				1.00	-0.10	0.09	0.02	0.27	-0.21
ΔIP_t^{OECD}					1.00	0.07	0.00	0.03	-0.11
$\Delta\sigma_t^{equity}$						1.00	0.26	0.51	0.19
$\Delta\sigma_t^{fx}$							1.00	-0.01	0.09
ΔVIX_t								1.00	0.06
Δliq_t									1.00

4.2. In-sample asymmetric predictive effects

Using the same set of predicting variables as in Chapter 3, I test for the asymmetric predictive effects in carry trade profits from each leg using a regression specified in Equation (3).

$$\overline{P}_t^{K_j} = \alpha + \beta_i^{LR} D_{t-i}^{LR} Z_{t-i} + \beta_i^{HR} D_{t-i}^{HR} Z_{t-i} + \gamma \overline{P}_{t-1}^{K_j} + \mu_t$$

$$(i = 1 \cdots 3, k = 1 \cdots 3,\ j = short, long), \quad (3)$$

where $\overline{P}_t^{K_{short}}$ ($\overline{P}_t^{K_{long}}$) is the profit from selling (buying) K low-yielding (high-yielding) currencies forward. Z_{t-i} is a single predictor similar to that in Equation (4). D_{t-i}^{LR} takes the value of 1 in a low-risk state ($r_{t-i}^{world} > 0$, $r_{t-i}^{CRB} > 0$, $\Delta\sigma_{t-i}^{equity} < 0$, $\Delta\sigma_{t-i}^{FX} < 0$), and the value of 0 otherwise. D_{t-i}^{HR} takes the value of 1 in a high-risk state ($r_{t-i}^{world} < 0$, $r_{t-i}^{CRB} < 0$, $\Delta\sigma_{t-i}^{equity} > 0$, $\Delta\sigma_{t-i}^{FX} > 0$) and the value of 0 otherwise. I conduct the Wald test against the null that $\beta_i^{LR} - \beta_i^{HR}$ equals zero and report the p-values for rejecting the null. A p-value below 0.1 suggests that drops and rises in the equity index or in commodity prices (increases and decreases in equity volatility or in currency volatility) mean different things for carry traders. Table 4.5 reports the estimation results.

The results in Table 4.5 suggest that the world equity return effect on future short-leg carry trade profits is asymmetric, while the equity volatility effect is symmetric. Drops in the world equity index significantly predict decreases in the short-leg profit of all three strategies two months later, with slope estimates on three $\beta_2^{HR'}s$ ranging between 0.22 and 0.29, and p-values below 0.01. Rises in the world equity index, however, do not significantly predict carry trade profits from low-yielding currencies (all slope estimates on $\beta_2^{LR'}s$ are insignificant for short-leg profits from all three strategies). This result suggests that, following drops in the world equity index, low-yielding currencies tend to appreciate against the U.S. dollar and result in decreases in profits from shorting low-yielding currencies. However, low-yielding currencies do not tend to depreciate against the U.S. dollar after the world equity index rises. When the model uses the world equity index return two months ago to predict the short-leg carry trade profit, Wald tests strongly reject the null hypothesis of a symmetric effect at significance levels below 0.05 (bolded fonts shown as p(wald) in Panel A).

In Chapter 3, I show that monthly changes in currency volatility significantly and negatively predict short-leg carry trade profits two months later. Results in Panel C of Table 4.5 indicate that, similar to the predictive effects from the world equity index return, the predictive effects from changes in currency volatility are also asymmetric. If currency volatility increases two months ago, carry trade profits from low-yielding currencies tend to decrease in this month (shown as the negative and significant slope estimates ranging between -4.95 and -5.22 for three $\beta_2^{HR}{}'s$ in Panel C). However, monthly decreases in currency volatility do not significantly predict the short-leg carry trade profits in two months' time. This asymmetric predictive effect is significant – the null hypothesis that predictive effects are symmetric at the two-month lag is rejected at significance levels between 0.03 and 0.08 (Panel C).

In contrast, the equity volatility effect on future carry trade profits from the short leg appears to be symmetrical. Monthly changes in equity volatility negatively predict all three short-leg carry trade profits two months later, regardless of the direction of volatility changes, with the slope estimates ranging between -1.25 to -1.72 for three $\beta_2^{HR}{}'s$ and three $\beta_2^{LR}{}'s$ and all six p-values below 0.05 (Panel B). Wald tests against the symmetric effect cannot reject the null hypothesis at a reasonable significance level (all three p-values are above 0.7).

Now, turning to the predictability in carry trade profits from high-yielding currencies, recall that in Chapter 3, I show that monthly changes in commodity prices, monthly changes in equity volatility and monthly changes in currency volatility significantly predict the long-leg carry trade profits in three months' time. Results in Panel D to F of Table 4.5 show that these predictors do not have significant asymmetric predictive ability. Drops in commodity prices tend to be followed by decreases in the long-leg carry trade profits three months later (with slope estimates for $\beta_3^{HR}{}'s$ ranging between 0.24 and 0.44 with p-values below 0.01, Panel D), while increases in commodity prices do not significantly predict long-leg carry trade profits. However, the difference between predictive coefficients in the high-risk and low-risk regimes is marginally significant, with p-values ranging between 0.08 and 0.22. The slope estimates on changes in equity volatility (Panel E) are negative and of similar sizes for both low- and high-risk regimes. Similarly, the predictive coefficients on changes in currency volatility for long-leg carry trade profits are both negative and of similar sizes for the two regimes (Panel F).

The signs of these significant slope estimates are the same with those from OLS regressions without high-risk and low-risk dummies (or, *symmetric models*), as well as similar to those from the VAR analysis in Section 3. The signs of coefficient estimates all make economic sense. First, for the short-leg payoff, the slope estimates on r_{t-2}^{world} are all positive in Table 5. This result is consistent with the intuition that after worldwide stock price drops investors demand more low-risk assets denoted in low-yielding currencies, leading to the appreciation of low-yielding currencies and decreases in profits from shorting these currencies. Second, slope estimates for $\Delta\sigma_{t-2}^{equity}$ ($\Delta\sigma_{t-2}^{FX}$) and $\Delta\sigma_{t-3}^{equity}$ ($\Delta\sigma_{t-3}^{FX}$) are uniformly negative. Increases (decreases) in the level of average global equity volatility or currency volatility predict drops (rises) in profits from the short leg two months later, as well as drops (rises) in profits from the long leg three months later.

The magnitude of the significantly asymmetric predictors is larger than their symmetric counterparts in Chapter 3. For example, Chapter 3 finds that if the monthly world equity index return changes by one standard deviation (4.59) in month $t-2$, on average the profit from shorting the three lowest-yielding currencies ($\overline{P}_t^{3_{short}}$, or *profits from short strategy 3*) has an annualised change of 5.35%, 0.6 standard deviation, in month t. Here, I consider drops and rises in the world equity index levels separately; if the world equity index return decreases by one standard deviation two months ago, the short-leg carry trade profit on average drops by 1.2 standard deviation. Similarly, when increases and decreases in currency volatility are considered separately, a one standard deviation increase in currency volatility tends to lead a one standard deviation drop in short-leg carry trade profits two months later – the size of predictive coefficient doubles that from the symmetric model in the previous chapter.

Table 4.5 Predicting carry trade profits in-sample with asymmetric effects

This table reports the coefficient estimates from the regression:

$$\overline{P}_t^{kj} = \alpha + \beta_i^{LR} D_{t-i}^{LR} Z_{t-i} + \beta_i^{HR} D_{t-i}^{HR} Z_{t-i} + \gamma \overline{P}_{t-1}^{kj} + \mu_t \quad (i = 1 \cdots 3, k = 1 \cdots 3,\ j = short, long), \qquad (3)$$

where $\overline{P}_t^{k_{short}}$ ($\overline{P}_t^{k_{long}}$) is the profit from selling (buying) K low-yielding (high-yielding) currencies forward. Z_{t-i} is a single predictor. The individual predictors for the short-leg carry trade profits are the world equity index return (r_{t-i}^{world}), changes in equity volatility ($\Delta\sigma_{t-i}^{equity}$) and changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$). The individual predictors for the long-leg carry trade profits and long/short carry trade profits are percentage changes in commodity prices (r_{t-i}^{CRB}), changes in equity volatility ($\Delta\sigma_{t-i}^{equity}$) and changes in currency volatility ($\Delta\sigma_{t-i}^{FX}$).

D_{t-i}^{LR} takes the value of 1 in a low-risk state ($r_{t-i}^{world} > 0$, $r_{t-i}^{CRB} > 0$, $\Delta\sigma_{t-i}^{equity} < 0$, $\Delta\sigma_{t-i}^{FX} < 0$), and the value of 0 otherwise. D_{t-i}^{HR} takes the value of 1 in a high-risk state ($r_{t-i}^{world} < 0$, $r_{t-i}^{CRB} < 0$, $\Delta\sigma_{t-i}^{equity} > 0$, $\Delta\sigma_{t-i}^{FX} > 0$) and the value of 0 otherwise. I conduct the Wald test against the null that $\beta_i^{LR} - \beta_i^{HR}$ equals zero and report the p-values for rejecting the null. A p-value below 0.1 suggests that drops and rises in the equity index and in commodity prices (increases and decreases in equity volatility and in currency volatility) mean different things for carry traders. Details of the carry trade strategies and predicting variables can be found in the main text.

The estimates for predictive coefficient β_1 are reported with two-sided heteroskedasticity consistent p-values and adjusted R^2 (shown as $\bar{R}^2$). p-values corresponding to a 10%, or better, significance level are bolded. The sample period runs from January 1985 to December 2011.

	β_1^{LR}	p	β_1^{HR}	p	$\bar{R}^2$	p (wald)	β_2^{LR}	p	β_2^{HR}	p	$\bar{R}^2$	p (wald)	β_3^{LR}	p	β_3^{HR}	p	$\bar{R}^2$	p (wald)
A. World equity index return ($\boldsymbol{r_{t-i}^{world}}$) predicts carry trade profits from the short leg																		
$\overline{P}_t^{1short}$	0.08	0.30	0.04	0.63	-0.2%	0.74	-0.07	0.36	0.29	**0.01**	4.9%	**0.03**	0.03	0.78	-0.04	0.68	-0.8%	0.66
$\overline{P}_t^{2short}$	0.09	0.19	-0.01	0.86	-0.2%	0.35	-0.03	0.71	0.20	**0.01**	3.0%	**0.07**	0.00	0.94	-0.07	0.45	-0.5%	0.59
$\overline{P}_t^{3short}$	0.09	0.19	-0.02	0.79	-0.3%	0.34	-0.03	0.66	0.20	**0.01**	3.1%	**0.07**	0.00	0.94	-0.07	0.39	-0.4%	0.55
B. Changes in equity volatility ($\boldsymbol{\Delta\sigma_{t-i}^{equity}}$) predicts carry trade profits from the short leg																		
$\overline{P}_t^{1short}$	1.13	0.34	-0.64	0.32	-0.1%	0.23	-1.56	**0.03**	-1.59	**0.04**	4.0%	0.98	-0.67	0.20	1.00	0.24	0.1%	0.13
$\overline{P}_t^{2short}$	1.03	0.28	-0.19	0.74	-0.2%	0.33	-1.72	**0.01**	-1.25	**0.01**	4.5%	0.62	-0.59	0.21	1.21	**0.07**	1.1%	**0.05**
$\overline{P}_t^{3short}$	1.10	0.27	-0.26	0.66	-0.1%	0.29	-1.70	**0.01**	-1.36	**0.01**	5.2%	0.72	-0.67	0.15	1.26	**0.06**	1.4%	**0.03**

	β_1^{LR}	p	β_1^{HR}	p	$\bar{R}^2$	p (wald)	β_2^{LR}	p	β_2^{HR}	p	$\bar{R}^2$	p (wald)	β_3^{LR}	p	β_3^{HR}	p	$\bar{R}^2$	p (wald)
C. Changes in currency volatility ($\Delta\boldsymbol{\sigma_{t-i}^{FX}}$) predicts carry trade profits from the short leg																		
$\overline{P}_t^{1short}$	5.22	**0.07**	-3.37	**0.08**	1.4%	**0.04**	0.34	0.86	-6.22	**0.01**	3.7%	**0.08**	1.73	0.39	0.16	0.94	-0.7%	0.62
$\overline{P}_t^{2short}$	4.07	**0.05**	-1.35	0.25	0.7%	**0.04**	0.85	0.58	-5.11	**<0.01**	3.0%	**0.03**	1.26	0.39	1.15	0.49	-0.4%	0.96
$\overline{P}_t^{3short}$	3.63	**0.07**	-1.34	0.24	0.4%	**0.06**	0.97	0.52	-4.95	**0.01**	2.9%	**0.03**	1.28	0.39	1.27	0.44	-0.3%	1.00
D. Changes in commodity prices ($\boldsymbol{r_{t-i}^{CRB}}$) predict carry trade profits from the long leg																		
$\overline{P}_t^{1long}$	0.03	0.79	0.14	0.33	0.5%	0.61	0.08	0.51	-0.01	0.94	0.2%	0.72	0.09	0.48	0.44	**<0.01**	6.1%	**0.08**
$\overline{P}_t^{2long}$	0.10	0.36	0.11	0.34	0.6%	0.96	0.08	0.40	0.05	0.74	0.4%	0.85	0.11	0.28	0.36	**<0.01**	6.2%	0.15
$\overline{P}_t^{3long}$	0.09	0.33	0.10	0.39	0.9%	0.94	0.11	0.24	0.00	0.98	0.9%	0.60	0.10	0.28	0.27	**<0.01**	5.1%	0.22
E. Changes in equity volatility ($\Delta\boldsymbol{\sigma_{t-i}^{equity}}$) predicts carry trade profits from the long leg																		
$\overline{P}_t^{1long}$	0.45	0.67	-0.69	0.46	0.4%	0.47	1.25	0.19	0.48	0.43	1.1%	0.53	-0.72	0.40	-1.28	0.11	1.9%	0.66
$\overline{P}_t^{2long}$	0.09	0.92	-0.44	0.68	0.0%	0.74	0.55	0.53	0.48	0.32	0.6%	0.95	-0.85	0.28	-1.09	0.10	2.4%	0.83
$\overline{P}_t^{3long}$	-0.26	0.72	-0.32	0.76	0.3%	0.97	0.54	0.43	0.59	0.22	1.2%	0.96	-0.92	0.19	-0.88	0.10	2.7%	0.97
F. Changes in currency volatility ($\Delta\boldsymbol{\sigma_{t-i}^{FX}}$) predicts carry trade profits from the long leg																		
$\overline{P}_t^{1long}$	-1.75	0.48	0.09	0.97	0.2%	0.67	-2.08	0.56	0.30	0.91	0.4%	0.65	-2.90	0.23	-3.27	0.29	2.1%	0.94
$\overline{P}_t^{2long}$	-3.84	0.07	1.19	0.65	0.8%	0.20	0.56	0.87	-0.19	0.93	0.1%	0.88	-3.73	0.11	-3.44	0.20	3.9%	0.95
$\overline{P}_t^{3long}$	-3.64	0.06	1.22	0.65	1.2%	0.21	-0.06	0.98	0.24	0.91	0.5%	0.94	-3.09	0.10	-2.22	0.30	3.1%	0.79

The model specified in Equation (3) tests for predictive effects for upside and downside movements separately. Thus, the adjusted R^2s are higher than their counterparts in Table 4.2 of Chapter 3 only when the predictive effects exhibit asymmetry. For example, the adjusted R^2s range between 3.1% and 4.9% when I use world equity index return conditioned on the direction of changes to predict the short-leg profits. These R^2s are higher than those reported for symmetric predictability in Chapter 3. The goodness-of-fit statistics also appear to be comparable to those reported for predictability in carry trade profits (for example, Bakshi and Panayotov, 2012, Tables 2 and 3; Adrian, Etula and Shin, 2009, Tables 1 and 2).

In Chapter 3, I find that changes in equity volatility subsume the predictive power of the world equity return – when these two variables are included together to predict the short-leg carry trade profits, the slope estimate of the world equity index return turns marginally significant. Now, I consider upward and downward movements in predictors separately and examine the marginal effect again. Table 4.6 presents the results. When I aggregate "bad" and "good" states (results reported in Table 4.2 of Chapter 3), changes in equity volatility subsume the predictive power of the world equity index return. By contrast, once I separate these two states, both the mean effect and volatility effect are robust to the other predictor. This result suggests that the world equity index return and changes in volatility contain different information. It also demonstrates the relevance of state-switching return predictability, as articulated by Ang and Timmermann (2011).

Table 4.6 Predicting carry trade profits in-sample with $\mathbf{r_{t-2}^{world}}$ and $\boldsymbol{\Delta\sigma_{t-2}^{equity}}$: without, or with, asymmetric effects

Panel A reports the slope coefficient estimates from the regression: $\overline{P}_t^{K_{short}} = \alpha + \boldsymbol{\beta_2}\, \boldsymbol{Z_{t-2}} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t$ $(K = 1 \cdots 3)$.

Panel B reports the coefficient estimates from the regression: $\overline{P}_t^{K_{short}} = \boldsymbol{\alpha} + \boldsymbol{\beta_2^{LR} D_{t-2}^{LR} Z_{t-2}} + \boldsymbol{\beta_2^{HR} D_{t-2}^{HR} Z_{t-2}} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t$ $(K = 1 \cdots 3)$,

where $\overline{P}_t^{K_{long}}$ ($\overline{P}_t^{K_{short}}$) is the profit to a U.S. investor from long (short) positions established at the end of month $t-1$ in a total of K highest- (lowest-) yielding currencies among the G-10 currencies, and $\boldsymbol{Z_{t-2}} = (r_{t-2}^{world}\ \Delta\sigma_{t-2}^{equity})'$

D_{t-i}^{LR} takes the value of 1 in a low-risk state, when $r_{t-i}^{world} > 0$ ($\Delta\sigma_{t-i}^{equity} < 0$), and the value of 0 otherwise. D_{t-i}^{HR} takes the value of 1 in a high-risk state, when $r_{t-i}^{world} < 0$ ($\Delta\sigma_{t-i}^{equity} > 0$), and the value of 0 otherwise. I conduct the Wald test against the null that $\beta^{LR} - \beta^{HR}$ equals zero and report the p-values for rejecting the null.

The estimates for predictive coefficients $\beta_2\ 's$, $\beta_2^{LR}{}'s$ and $\beta_2^{HR}{}'s$ are reported with two-sided heteroskedasticity consistent p-values and adjusted R^2 (shown as $\bar{R}^2$). p-values corresponding to a 10%, or better, significance level are bolded. The sample period runs from January 1985 to December 2011.

A. Predicting carry trade profits with two predictors without asymmetric effects

	r_{t-2}^{world}	p	$\Delta\sigma_{t-2}^{equity}$	p	$\bar{R}^2$
$\overline{P}_t^{1short}$	0.07	0.16	-1.30	**<0.01**	5.7%
$\overline{P}_t^{2short}$	0.05	0.18	-1.21	**<0.01**	5.6%
$\overline{P}_t^{3short}$	0.05	0.22	-1.29	**<0.01**	6.4%

B. Predicting carry trade profits with two predictors with asymmetric effects

	$r_{t-2}^{world} D_{t-2}^{LR}$	p	$\Delta\sigma_{t-2}^{equity} D_{t-2}^{LR}$	p	$r_{t-2}^{world} D_{t-2}^{HR}$	p	$\Delta\sigma_{t-2}^{equity} D_{t-2}^{HR}$	p	$\bar{R}^2$
$\overline{P}_t^{1short}$	-0.09	0.25	-1.89	**0.01**	0.29	**0.02**	-0.28	0.60	7.6%
$\overline{P}_t^{2short}$	-0.04	0.54	-1.84	**0.01**	0.19	**0.01**	-0.39	0.38	6.4%
$\overline{P}_t^{3short}$	-0.05	0.51	-1.77	**0.01**	0.17	**0.02**	-0.59	0.20	7.0%

5. Rolling-window analysis of asymmetric predictability

Full-sample regressions reveal that some variables predict carry trade profits more strongly in the high-risk regime than in the low-risk regime, and the difference in predictive coefficients in the two regimes is significant.

An important question to ask is how the discussed asymmetric predictive effects change over time. For these significant and asymmetric in-sample predictive relations identified in Table 4.5, I run 10-year rolling window regressions using Equation (3), and plot the slope estimates over time in Figure 4.2.

The “bad” market effects have been stable over the sample period, for both the carry trade profits from the short leg and those from the long leg. The slope estimates on the decreases in world equity index lagged by two months have been consistently positive (Panel A in Figure 4.2). Similarly, the slope estimates on increases in currency volatility as a predictor for the short-leg profits have always been in negative territory (Panel B. in Figure 4.2). The slope estimates on drops in commodity prices lagged by three months have also been consistently positive (Panel C. in Figure 4.2).

6. Out-of-sample tests and economic significance asymmetric predictability

In Chapter 3, I show that carry traders could have used the world equity index return, changes in equity volatility, changes in currency volatility and changes in commodity prices to deliver more accurate forecasting than simply using historical means as the forecast. Could an investor have used the discussed asymmetric prediction model in this chapter to deliver better forecasting than historical mean models, or even further improve the accuracy of the forecast relative to symmetric models? In order to answer this question, I compare the out-of-sample (OoS) R^2 statistics, as in Goyal and Welch (2008), from the asymmetric prediction models specified as Equation (3) in this chapter, using historical means as the benchmark first and then using predictions from symmetric models as the benchmark. The $OoS\ R^2$ is computed according to Equation (4) in Chapter 3. I also conduct a significance test for the out-of-sample outperformance using an adjusted mean-squared prediction error statistic (MSPE-adjusted) developed by Clark and West (2007), which was introduced in Chapter 3.

Figure 4.2 Rolling-window regressions: asymmetric predictive effects

I plot asymmetric predictive slope estimates from rolling predictive regressions as specified in the equations below across time.

$$\overline{P}_t^{3short} = \alpha + \beta_2^{LR} D_{t-2}^{LR} r_{t-2}^{world} + \beta_i^{HR} D_{t-2}^{HR} r_{t-2}^{world} + \gamma \overline{P}_{t-1}^{3short} + \mu_t$$

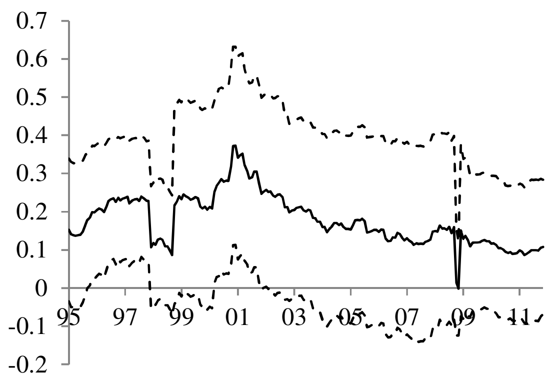
$$\overline{P}_t^{3short} = \alpha + \beta_2^{LR} D_{t-2}^{LR} \Delta\sigma_{t-2}^{FX} + \beta_2^{HR} D_{t-2}^{HR} \Delta\sigma_{t-2}^{FX} + \gamma \overline{P}_{t-1}^{3short} + \mu_t$$

$$\overline{P}_t^{3long} = \alpha + \beta_3^{LR} D_{t-3}^{LR} r_{t-3}^{CRB} + \beta_3^{HR} D_{t-3}^{HR} r_{t-3}^{CRB} + \gamma \overline{P}_{t-1}^{3long} + \mu_t \quad ,$$

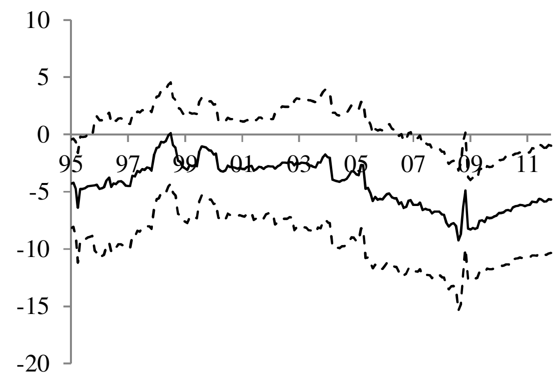
where $\overline{P}_t^{3short}$ ($\overline{P}_t^{3long}$) is the profit from selling (buying) 3 low-yielding (high-yielding) currencies forward. Z_{t-i} is a single predictor similar to that in Equation (4). D_{t-i}^{LR} takes the value of 1 in a low-risk state ($r_{t-i}^{world} > 0$, $r_{t-i}^{CRB} > 0$, $\Delta\sigma_{t-i}^{equity} < 0$, $\Delta\sigma_{t-i}^{FX} < 0$), and the value of 0 otherwise. D_{t-i}^{HR} takes the value of 1 in a high-risk state ($r_{t-i}^{world} < 0$, $r_{t-i}^{CRB} < 0$, $\Delta\sigma_{t-i}^{equity} > 0$, $\Delta\sigma_{t-i}^{FX} > 0$) and the value of 0 otherwise.

I choose a window size of 10 years (120 monthly observations). The sample period runs from January 1985 to December 2011. The solid line represents the slope estimates and dashed lines represent 90% confidence bands.

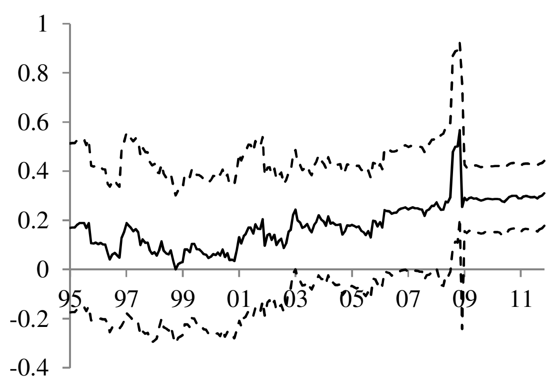
A. Predicting $\overline{P}_t^{3short}$: Slope estimates on $r_{t-2}^{world} D_{t-2}^{HR}$



B. Predicting $\overline{P}_t^{3short}$: Slope estimates on $D_{t-2}^{HR} \Delta\sigma_{t-2}^{FX}$



C. Predicting $\overline{P}_t^{3long}$: Slope estimates on$D_{t-3}^{HR} r_{t-3}^{CRB}$



Because decreases, but not increases, in the world equity index return significantly predict the short-leg carry trade profits, a prediction model that includes predictors in both the low-risk and high-risk regime may introduce additional noise and hence deliver poorer results than the symmetric model. Thus, I test the out-of-sample performance of two types of asymmetric models. The first type of asymmetric prediction model includes predictors in both regimes and the second type only includes predictors in the high-risk regime. Panel A of Table 4.7 reports out-of-sample R^2s (Goyal and Welch, 2008) and MSPE-adjusted one-sided p-values (Clark and West, 2007) for asymmetric predictability of carry trade profits, benchmarked against historical mean models. In these out-of-sample tests, I use predictors lagged by two months to predict short-leg profits and three months to predict the long-leg profits, because the question here is whether these significant in-sample predictors deliver significant out-of-sample results. Asymmetric (1) refers to models using the following regressions, including predictors in both high-risk and low-risk regimes:

$$\overline{P}_t^{K_{short}} = \alpha + \beta_2^{LR} D_{t-2}^{LR} Z_{t-2} + \beta_2^{HR} D_{t-2}^{HR} Z_{t-2} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3) \tag{4}$$

$$\overline{P}_t^{K_{long}} = \alpha + \beta_3^{LR} D_{t-3}^{LR} Z_{t-3} + \beta_3^{HR} D_{t-3}^{HR} Z_{t-3} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3) \tag{5}$$

Asymmetric (2) in Table 4.7 refers to models that use the following regressions, including only predictors in the high-risk regime:

$$\overline{P}_t^{K_{short}} = \alpha + D_{t-2}^{HR} Z_{t-2} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3) \tag{6}$$

$$\overline{P}_t^{K_{long}} = \alpha + \beta_3^{HR} D_{t-3}^{HR} Z_{t-3} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3) \tag{7}$$

In order to facilitate comparison, on columns titled *symmetric*, I also report out-of-sample results from symmetric prediction models as specified in Chapter 3:

$$\overline{P}_t^{K_{short}} = \alpha + \beta_2 \ Z_{t-2} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3) \tag{8}$$

$$\overline{P}_t^{K_{long}} = \alpha + \beta_3 \ Z_{t-3} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3)\ , \tag{9}$$

where $\overline{P}_t^{K_{short}}$ ($\overline{P}_t^{K_{long}}$) is the profit from selling (buying) K low-yielding (high-yielding) currencies forward. Z_{t-i} is a single predictor. The individual predictors for the short-leg carry trade profits are the world equity index return (r_{t-2}^{world}), changes in equity volatility ($\Delta\sigma_{t-2}^{equity}$) and changes in currency volatility ($\Delta\sigma_{t-2}^{FX}$). The individual predictors for the long-leg carry trade profits and long/short carry trade profits are percentage changes in commodity prices (r_{t-3}^{CRB}), changes in equity volatility ($\Delta\sigma_{t-3}^{equity}$) and changes in currency volatility ($\Delta\sigma_{t-3}^{FX}$). D_{t-i}^{LR} takes the value of 1 in a low-risk state ($r_{t-i}^{world} > 0, r_{t-i}^{CRB} > 0, \Delta\sigma_{t-i}^{equity} < 0, \Delta\sigma_{t-i}^{FX} < 0$), and the value of 0 otherwise. D_{t-i}^{HR} takes the value of 1 in a high-risk state ($r_{t-i}^{world} < 0, r_{t-i}^{CRB} < 0, \Delta\sigma_{t-i}^{equity} > 0, \Delta\sigma_{t-i}^{FX} > 0$) and the value of 0 otherwise.

Regardless of whether the forecast is from asymmetric model (1) or asymmetric model (2), when predictions are benchmarked against historical mean, out-of-sample performance appears to be good and comparable to the performance of symmetric models. $OoS\ R^{2\prime}s$ from asymmetric model (1) and (2) in Panel A of Table 4.7 range between 1.95% and 7.84% for the short-leg profits and between 0.78% and 8.49% for the long-leg profits. Although the $OoS\ R^2$s of asymmetric model (1) and (2) are comparable to those reported in return predictability studies[27] for return predictability, they tend to be similar to the $OoS\ R^2$s of symmetric prediction models. For example, symmetric models that use the world equity index returns two months ago to predict the short-leg profit deliver $OoS\ R^2$s between 3.57 and 4.22 (in the first three cells on the first column in Panel A of Table 4.7). $OoS\ R^2$s from their asymmetric counterparts (1) and (2) are very similar, ranging between 1.95 and 4.15 and between 3.09 and 5.08, respectively (Panel A of Table 4.7).

The most noticeable improvements in out-of-sample performance occur in the asymmetric models that use either drops and rises in currency volatility (asymmetric model (1)) or only rises in currency volatility (asymmetric model (2)) to predict carry trade profits from the short leg. $OoS\ R^2$s from symmetric models that use changes in currency volatility to predict short-leg carry trade profits range between 2.75 and 3.34. In contrast, asymmetric model (1) and (2) deliver $OoS\ R^2$s ranging between 5.50 and 6.07 and between 5.54 and 6.79, respectively.

[27] For example, Bakshi and Payayotov (2012), Goyal and Welch (2008), Campbell and Thompson (2008) and Rapach, Strauss and Zhou (2012).

To a lesser extent, asymmetric models that predict long-leg carry trade profits with only drops in commodity prices, or asymmetric model (2), also deliver higher $OoS\ R^2$s, ranging between 5.79 and 8.59, higher than those from symmetric models (ranging between 5.29 and 6.80). However, when both rises and drops in commodity prices are considered, the prediction models (asymmetric model (1)) do not deliver better results than symmetric models.

The MSPE-adjusted one-sided p-values are consistent with results from $OoS\ R^2$ analysis. MSPE-adjusted one-sided p-values from asymmetric prediction models are generally higher than those from symmetric models, suggesting that asymmetric models do not deliver better forecasting out-of -sample than symmetric models.

I also compare trading outcomes of market-timing strategies based on predictions from asymmetric model (1) and (2) with those based on predictions from symmetric models. In a market-timing strategy, the trading decision is based on a one-step-ahead prediction of carry trade profits. An investor goes ahead with a carry trade if the predicted payoff is positive; otherwise, he or she refrains from a carry trade. This decision rule is applied to each leg of a carry trade. The related outcomes are reported Table 4.8.

Table 4.7 Asymmetric predictability in carry trades: out-of-sample performance

This table reports out-of-sample R^2s (Goyal and Welch, 2008) and MSPE-adjusted one-sided p-values (Clark and West, 2007) for asymmetric predictability of carry trade profits.

Panel A reports out-of-sample results where predictions from asymmetric models are benchmarked against historical means. Panel B reports out-of-sample results where predictions from asymmetric models are benchmarked against predictions from symmetric models.

Column heading asymmetric (1) refers to prediction models that forecast with variables in both high-risk and low-risk regimes, as specified in the following equations:

$$\overline{P}_t^{K_{short}} = \alpha + \beta_2^{LR} D_{t-2}^{LR} Z_{t-2} + \beta_2^{HR} D_{t-2}^{HR} Z_{t-2} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3), \qquad (4)$$

$$\overline{P}_t^{K_{long}} = \alpha + \beta_3^{LR} D_{t-3}^{LR} Z_{t-3} + \beta_3^{HR} D_{t-3}^{HR} Z_{t-3} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3), \qquad (5)$$

Column heading asymmetric (2) refers to prediction models that forecast only with variables in the high-risk regime, as specified in the following equations:

$$\overline{P}_t^{K_{short}} = \alpha + D_{t-2}^{HR} Z_{t-2} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3), \qquad (6)$$

$$\overline{P}_t^{K_{long}} = \alpha + \beta_3^{HR} D_{t-3}^{HR} Z_{t-3} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3), \qquad (7)$$

Column heading symmetric refers to out-of-sample results from symmetric prediction models as specified in Chapter 3, as specified in the following equations:

$$\overline{P}_t^{K_{short}} = \alpha + \beta_2 \ Z_{t-2} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3), \qquad (8)$$

$$\overline{P}_t^{K_{long}} = \alpha + \beta_3 \ Z_{t-3} + \gamma \overline{P}_{t-1}^{K_{short}} + \mu_t \quad (K = 1 \cdots 3), \qquad (9)$$

The individual predictors for the short-leg carry trade profits are the world equity index return (r_{t-2}^{world}), changes in equity volatility ($\Delta\sigma_{t-2}^{equity}$) and changes in currency volatility ($\Delta\sigma_{t-2}^{FX}$). The individual predictors for the long-leg carry trade profits and long/short carry trade profits are percentage changes in commodity prices (r_{t-3}^{CRB}), changes in equity volatility ($\Delta\sigma_{t-3}^{equity}$) and changes in currency volatility ($\Delta\sigma_{t-3}^{FX}$).

D_{t-i}^{LR} takes the value of 1 in a low-risk state ($r_{t-i}^{world} > 0$, $r_{t-i}^{CRB} > 0$, $\Delta\sigma_{t-i}^{equity} < 0$, $\Delta\sigma_{t-i}^{FX} < 0$), and the value of 0 otherwise. D_{t-i}^{HR} takes the value of 1 in a high-risk state ($r_{t-i}^{world} < 0$, $r_{t-i}^{CRB} < 0$, $\Delta\sigma_{t-i}^{equity} > 0$, $\Delta\sigma_{t-i}^{FX} > 0$) and the value of 0 otherwise.

The first 180 monthly observations are used to estimate the prediction models and forecast the first one-month-ahead carry trade profits, then models are re-estimated every month using all past observations to predict carry trade payoffs in a new month. The sample period is from January 1985 to December 2011.

The $OoS\ R^2$ is computed as in Goyal and Welch (2008).

$$OoS\ R^2 = 1 - \frac{MSE(prediction\ model)}{MSE(benchmark\ model)} = 1 - \frac{\sum_{j=1}^{n} (\widehat{\theta_t} - \overline{P}_t\ )^2}{\sum_{j=1}^{n} (\theta_t - \overline{P}_t\ )^2} \ ,$$

where $\widehat{\theta}_t$ is the predicated carry trade payoff in month t and θ_t is the historical average payoff. $\overline{P}_t$ is the realised carry trade payoff in month t.

The MSPE-adjusted one-sided p-values are obtained by regressing $f_t = (\overline{P}_t^{k_j} - \theta_t)^2 - [\left(\overline{P}_t^{k_j} - \widehat{\theta}_t\right)^2 - \left(\theta_t - \hat{\theta}\right)^2]$ on a constant. p-values below 0.10 are shown in bold font.

	symmetric			asymmetric (1)			asymmetric (2)		
A. Benchmarked against mean models									
Predicting short-leg profits									
Predictors	r_{t-2}^{world}	$\Delta\sigma_{t-2}^{equity}$	$\Delta\sigma_{t-2}^{FX}$	r_{t-2}^{world}	$\Delta\sigma_{t-2}^{equity}$	$\Delta\sigma_{t-2}^{FX}$	r_{t-2}^{world}	$\Delta\sigma_{t-2}^{equity}$	$\Delta\sigma_{t-2}^{FX}$
$OoS\ R^2$ (%)									
$\overline{P}_t^{1short}$	4.22	7.95	3.34	4.16	7.02	6.07	5.08	6.23	6.79
$\overline{P}_t^{2short}$	4.06	8.21	2.55	2.83	7.59	5.50	3.91	5.37	5.54
$\overline{P}_t^{3short}$	3.57	8.42	2.75	1.95	7.84	5.66	3.03	5.44	5.64
MSPE adjusted one-sided p-values									
$\overline{P}_t^{1short}$	**0.06**	**0.04**	0.13	**0.10**	**0.02**	0.13	**0.09**	**0.08**	0.12
$\overline{P}_t^{2short}$	**0.04**	**0.02**	0.12	**0.09**	**0.01**	**0.10**	**0.07**	**0.06**	**0.10**
$\overline{P}_t^{3short}$	**0.05**	**0.02**	0.11	0.11	**0.01**	0.11	**0.08**	**0.07**	**0.10**
Predicting long-leg profits									
Predictors	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$
$OoS\ R^2$ (%)									
$\overline{P}_t^{1long}$	6.46	1.45	1.91	6.33	1.05	0.29	8.49	1.17	1.14
$\overline{P}_t^{2long}$	6.80	1.88	2.31	5.58	1.38	1.01	8.59	1.32	1.94
$\overline{P}_t^{3long}$	5.29	1.60	1.19	4.36	1.18	0.28	5.77	1.02	0.78
MSPE adjusted one-sided p-values									
$\overline{P}_t^{1long}$	**0.05**	**0.04**	**0.09**	**0.07**	**0.10**	0.24	**0.09**	**0.08**	0.17
$\overline{P}_t^{2long}$	**0.04**	**0.01**	**0.09**	**0.05**	**0.04**	0.17	**0.08**	**0.03**	0.16
$\overline{P}_t^{3long}$	**0.03**	**0.03**	0.14	**0.04**	**0.07**	0.24	**0.06**	**0.08**	0.23

symmetric		asymmetric (1)			asymmetric (2)	
B. Benchmarked against symmetric models						
Predicting short-leg profits						
Predictors	r_{t-2}^{world}	$\Delta\sigma_{t-2}^{equity}$	$\Delta\sigma_{t-2}^{FX}$	r_{t-2}^{world}	$\Delta\sigma_{t-2}^{equity}$	$\Delta\sigma_{t-2}^{FX}$
$OoS\ R^2$ (%)						
$\overline{P}_t^{1short}$	-0.06	-1.00	2.82	0.90	-1.87	3.57
$\overline{P}_t^{2short}$	-1.29	-0.68	3.02	-0.16	-3.09	3.07
$\overline{P}_t^{3short}$	-1.68	-0.64	3.00	-0.56	-3.25	2.97
MSPE adjusted one-sided p-values						
$\overline{P}_t^{1short}$	0.21	0.29	**0.08**	0.23	0.50	**0.07**
$\overline{P}_t^{2short}$	0.35	0.43	**0.07**	0.28	0.35	**0.07**
$\overline{P}_t^{3short}$	0.36	0.40	**0.08**	0.31	0.38	**0.09**
Predicting long-leg profits						
$OoS\ R^2$ (%)	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$
$\overline{P}_t^{1long}$	-0.13	-0.40	-1.65	2.18	-0.28	-0.78
$\overline{P}_t^{2long}$	-1.30	-0.51	-1.33	1.93	-0.57	-0.37
$\overline{P}_t^{3long}$	-0.98	-0.43	-0.92	0.51	-0.60	-0.42
MSPE adjusted one-sided p-values						
$\overline{P}_t^{1long}$	0.41	0.37	**0.03**	0.12	0.40	0.31
$\overline{P}_t^{2long}$	**0.07**	0.24	**0.02**	**0.07**	0.18	0.45
$\overline{P}_t^{3long}$	**0.10**	0.13	**0.03**	0.15	0.17	0.46

Consistent with the findings from tests using out-of-sample $R^2{}'s$ and the MSPE-adjusted one-sided p-values, trading decisions based on predictions from asymmetric models do not lead to large improvements in trading outcomes, compared with when predictions are made from symmetric models. For example, a simple strategy that always shorts the lowest-yielding currency ($\overline{P}_t^{3short}$) generates an annualized profit of -1.6% during my sample period (the first column of Table 8). In Chapter 3, I show that market-timing strategy using a symmetric model, that uses the world equity index return two months ago to predict the short-leg profits, results in an average annualized profit of 1.14% (the second column of Table 8). If one trades based on predicted short-leg profits from asymmetric model (1) that uses the rises and drops in world equity index as predictors, he or she would have made an average annual loss of 0.14%, which is lower than trading profits conditional on predictions from the symmetric model. If one makes trading decisions based on predictions from asymmetric model (2), using only drops in world equity index return as a predictor, he or she would have made an annual average profit of 1.66% – this average profit is marginally higher than the 1.14% where one uses a symmetric prediction model, but the asymmetric model leads to less positively skewed trading outcomes and fewer correct trading signals. The skewness of trading outcomes using asymmetric model (2) is 0.60, lower than the 0.87 from the symmetric model.

Table 4.8 Predicting carry trade payoff with asymmetric models: economic significance

This table reports the annual mean, Sharpe ratio and skewness of monthly profits (annualised) from simple strategies and market-timing strategies. One always goes ahead with carry trades in simple strategies. Profits from market-timing strategies are conditional on predicted carry trade using models specified in Equations (4) to (9).

Using the market-timing carry trade strategy, one goes ahead with the carry trade if the predicted payoffs are positive and refrains from carry trades otherwise. The sample period is from January 1985 to December 2011. The first 180 monthly observations are used to estimate prediction models and forecast the first one-month-ahead carry trade payoffs, then the models are re-estimated every month using all past observations to predict carry trade payoffs in a new month.

	simple	symmetric			asymmetric (1)			asymmetric (2)		
Predicting short-leg profits										
Predictors		r_{t-2}^{world}	$\Delta\sigma_{t-2}^{equity}$	$\Delta\sigma_{t-2}^{FX}$	r_{t-2}^{world}	$\Delta\sigma_{t-2}^{equity}$	$\Delta\sigma_{t-2}^{FX}$	r_{t-2}^{world}	$\Delta\sigma_{t-2}^{equity}$	$\Delta\sigma_{t-2}^{FX}$
Mean										
$\overline{P}_t^{1short}$	-1.60	1.14	-0.10	-0.38	-0.14	1.55	0.36	1.66	0.53	0.84
$\overline{P}_t^{2short}$	-0.99	1.66	1.00	0.46	0.45	2.38	1.07	1.36	1.21	0.89
$\overline{P}_t^{3short}$	-1.03	1.23	0.69	0.13	-0.01	1.35	0.89	0.80	0.71	0.72
Sharpe-ratios										
$\overline{P}_t^{1short}$	-0.18	0.21	-0.02	-0.07	-0.02	0.29	0.05	0.27	0.08	0.12
$\overline{P}_t^{2short}$	-0.12	0.31	0.17	0.08	0.07	0.49	0.16	0.22	0.18	0.13
$\overline{P}_t^{3short}$	-0.13	0.23	0.12	0.02	0.00	0.25	0.14	0.13	0.11	0.11
Skewness										
$\overline{P}_t^{1short}$	-1.10	0.87	0.10	-0.07	-0.22	0.48	0.09	0.60	0.14	0.07
$\overline{P}_t^{2short}$	-0.45	0.47	0.20	0.37	0.04	1.06	-0.02	0.33	0.20	0.00
$\overline{P}_t^{3short}$	-0.34	0.51	0.20	0.71	0.26	0.41	0.25	0.35	0.21	0.27

	simple	symmetric			asymmetric (1)			asymmetric (2)		
Predicting long-leg profits										
Predictors	simple	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$
$\overline{P}_t^{1\,long}$	8.88	9.53	9.22	8.96	9.53	8.68	7.90	10.07	8.68	8.96
$\overline{P}_t^{2\,long}$	7.19	8.52	7.59	6.50	7.76	7.59	6.73	8.63	7.59	7.10
$\overline{P}_t^{3\,long}$	5.65	7.18	5.79	4.82	7.18	5.79	4.99	6.94	5.79	4.99
Sharpe-ratios										
$\overline{P}_t^{1\,long}$	0.68	0.82	0.71	0.73	0.82	0.67	0.61	0.84	0.67	0.73
$\overline{P}_t^{2\,long}$	0.59	0.83	0.63	0.60	0.73	0.63	0.62	0.77	0.63	0.65
$\overline{P}_t^{3\,long}$	0.52	0.77	0.54	0.48	0.77	0.54	0.50	0.69	0.54	0.50
Skewness										
$\overline{P}_t^{1\,long}$	-0.52	-0.38	-0.54	-0.29	-0.38	-0.54	-0.51	-0.29	-0.54	-0.29
$\overline{P}_t^{2\,long}$	-0.49	-0.37	-0.52	-0.51	-0.53	-0.52	-0.53	-0.33	-0.52	-0.52
$\overline{P}_t^{3\,long}$	-0.71	-0.79	-0.75	-0.93	-0.79	-0.75	-0.94	-0.74	-0.75	-0.94

7. Conclusion

Using VAR models, I investigate dynamic predictive relations among carry trade profits from each leg, the world equity index return and changes in commodity prices. Results from the VAR analysis suggest that commodity price movements Granger-cause changes in the world equity index return and Granger-cause carry trade profits from longing the high-yielding currencies. Changes in the world equity index levels, but not changes in commodity prices, Granger-cause carry trade profits from shorting the low-yielding currencies. Plots of impulse response further reveal that the delayed responses in carry trade profits to shocks to commodity prices and to shocks to equity prices are temporary. The pattern of impulse responses appears to be consistent with a delayed reaction of investors to information contained in the world equity indices and in commodity prices.

Drops, but not rises, in the world equity index predict decreases in carry trade profits from the short leg. Changes in currency volatility also predict the short-leg carry trade profits in a bad market, when volatility increases, but not in a good market. Similarly, decreases, but not increases, in commodity prices predict carry trade profits from the long leg. In contrast, changes in equity volatility do not have any asymmetric effect on future carry trade profits.

Prediction models that utilize these in-sample significant asymmetric effects deliver good out-of-sample performance, when they are benchmarked against models that use historical means as predicted carry trade profits. However, when they are benchmarked against symmetric prediction models from Chapter 3, further improvements in prediction accuracy is very limited.

Chapter 5 Conclusion

Each of the three essays contained in this dissertation adds new evidence for short-run return predictability, each in a different respect.

In the first essay, I studied the puzzling momentum profits, which are a result of the short-run predictability, or positive autocorrelations, in stock returns.[1] I show that asymmetric tail risks may render stock momentum strategies unattractive. Momentum strategies, though appearing to be profitable, may not be employed by investors should they be concerned about extreme tail risks. It is possible that asymmetric tail risks are also present in returns from strategies that take advantage of other financial anomalies. Hence, a natural extension of the first essay can be an investigation of tail risks related to other well-known financial anomalies.

The second essay investigated the short-run predictability in carry trade profits. I show that low- and high-yielding currencies are both predictable, and that the predictability may be a result of information gradually flowing from commodity markets to currency markets and from equity markets to currency markets. The predictive effects are short-lived and lead to many predicted losses in carry trades. Thus, risk does not seem to explain the discussed predictability. More direct tests on the gradual information diffusion hypothesis provide evidence that is consistent with this behavioural explanation. First, as the size of lags between predictors and carry trade profits lengthens, explanatory powers of prediction models increase, peak and quickly drop. Second, if a variable, such as changes in commodity prices, strongly and positively predicts carry trade profits, it tends to also positively and strongly predict the industrial production growth. The strong correlation between a variable's ability in predicting carry trade profits and its ability in forecasting industrial

[1] Cochrane (2005).

production growth suggests that the discussed predictability may be related to gradual diffusion of information related to economic fundamentals.

In the third essay, I took the work in the second essay a step further and investigated whether carry trades, stocks and commodities cross-predict each other. I model the dynamic relations with vector autoregressive models and find that predictive effects go from commodities to stocks, from commodities to high-yielding currencies and from stock to low-yielding currencies. This essay also documents an asymmetric effect from movements in equity indices (commodity prices) on future returns from shorting low-yielding (high-yielding) currencies – drops in stock (commodity) price strongly predict the appreciation of low-yielding currencies (depreciation of high-yielding currencies), but stock (commodity) price increases do not significantly predict the depreciation of low-yielding currencies (appreciation of high-yielding currencies). Similarly, the effect from changes in currency volatility on future profits from shorting low-yielding currencies is also asymmetric. This finding suggests that stock markets serve as a “bad” market barometer for carry trades that short low-yielding currencies. To a lesser extent, commodity markets also serve as a “bad” market indicator for high-yielding currencies. If currency volatility increases this month, low-yielding currencies tend to appreciate in two months’ time, resulting in drops in short-leg carry trade profits. If there is a large drop in the world equity index in one month (that is, the world equity index return is more than half a standard deviation below the mean), it is time to unwind short positions in low-yielding currencies in the following month. While all other significant predictors for carry trade profits display asymmetric ability, both rises and drops in equity volatility negatively predict carry trade profits from low-yielding currencies two months later. A possible extension of the two essays on carry trade predictability is to include emerging market currencies in the investable currency universe, in order to assess whether carry trade predictability as discussed in the last two essays in this dissertation is common to all currencies.

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Appendices

Appendix 3.A. Funding and Investment Currencies in Carry Trade

This table reports the number of months when each currency has been the highest-interest (lowest-interest), or among the two or three highest-interest (lowest-interest) currencies, over the sample period of January 1985 to December 2011 (324 months in total).

In order to assess the relative attractiveness of a currency as a funding, or investment, currency in a carry trade, I rank the realizable interest rate differentials against the USD, inferred from corresponding bid and ask forward and spot quotes:

$$idiff_t = \begin{cases} \dfrac{S_t^{ask}}{F_t^{bid}} - 1 & if\ F_t^{bid} > S_t^{ask} \\ \dfrac{S_t^{bid}}{F_t^{ask}} - 1 & if\ F_t^{ask} < S_t^{bid} \\ 0 & otherwise \end{cases},$$

where S_t denotes the spot exchange rate at the end of month t and F_t denotes the forward price at the end of month t for delivery at the end of month $t+1$. The USD has an interest rate differential of zero for all periods.

	Funding currencies (# of months)			Investment currencies (# of months)		
	Lowest	Two lowest	Three lowest	Three highest	Two highest	Highest
AUD, Australian dollar	0	2	2	181	143	72
CAD, Canadian dollar	1	3	9	32	10	6
CHF, Swiss franc	39	170	187	4	3	1
EUR, euro	7	25	103	22	11	6
GBP, British pound	0	1	2	149	88	27
JPY, Japanese yen	192	225	232	3	2	1
NOK, Norwegian krone	1	1	6	131	74	46
NZD, New Zealand dollar	0	0	0	203	187	108
SEK, Swedish krona	2	4	12	79	60	40
USD, U.S. dollar	82	135	202	98	53	17

Appendix 3.B. Summary of Predictors for Carry Trade Profits

This appendix describes the predictors of currency carry trade profits investigated in this study.

1. $\Delta\boldsymbol{\sigma}_{\boldsymbol{t}}^{\boldsymbol{equity}}$ [1]: changes in average equity volatility, as a proxy for uncertainty in global equity markets, based on Lustig, Roussanov and Verdelhan (2012). A country's equity volatility in month $\boldsymbol{t}$ is computed as the standard deviation of daily stock market index returns, and the average equity return volatility is the cross-sectional mean of these country volatility series in this study. $\Delta\boldsymbol{\sigma}_{\boldsymbol{t}}^{\boldsymbol{equity}}$, or change in average equity volatility, is the difference between average equity volatility in month $\boldsymbol{t}$ and month $\boldsymbol{t-1}$. Lustig, Roussanov and Verdelhan (2012) employ $\Delta\boldsymbol{\sigma}_{\boldsymbol{t}}^{\boldsymbol{equity}}$ in cross-sectional asset pricing test and reveal that low (high) interest rate currencies offer high (low) returns when average equity volatility increases.
2. $\Delta\boldsymbol{\sigma}_{\boldsymbol{t}}^{\boldsymbol{FX}}$: changes in average currency volatility, as a proxy for uncertainty in global currency markets, based on Menkhoff, Sarno, Schmeling and Schrimpf (2012). For each G-10 currency included in this study, I calculate monthly volatility as the standard deviation of daily exchange rate changes against the U.S. dollar over a month. The monthly currency volatility averaged across G-10 currencies is the average currency volatility. $\Delta\boldsymbol{\sigma}_{\boldsymbol{t}}^{\boldsymbol{FX}}$ is the difference between average currency volatility in month $\boldsymbol{t}$ and month $\boldsymbol{t-1}$. It explains cross-sectional currency returns (Menkhoff, Sarno, Schmeling and Schrimpf, 2012).
3. $\boldsymbol{r}_{\boldsymbol{t}}^{\boldsymbol{world}}$: MSCI world index percentage returns, as a proxy for world equity market performance, based Ranaldo and Söderlind (2010), which document that the Swiss franc and Japanese yen appreciate against the U.S. dollar when US stock prices decrease.

[1] Because volatility series including $\sigma_t^{equity}, \sigma_t^{fx}$ and VIX has high first-order autocorrelation, predicting variables are the innovations in volatility (similar approaches are employed by Ang, Hodrick, Xing and Zhang, 2006, Lustig, Roussanov and Verdelhan, 2012, and Menkhoff, Sarno, Schmeling and Schrimpf, 2012).

4. r_t^{CRB}: CRB industrial raw commodity spot index return, based on Bakshi and Panayotov (2012). They find that r_t^{CRB} predicts dynamic carry trade profits both in-sample and out-of-sample.
5. Δliq_t : change in global liquidity, based on Brunnermeier, Nagel and Pedersen (2008) and Bakshi and Panayotov (2012). They document that change in global liquidity has some predictive power for carry trade profits, in addition to r_t^{crb} and $\Delta\sigma_t^{fx}$. I compute an average of the equivalent of TED spread (3 month LIBOR minus 3 month T-bill yields) across the G-10 currencies. Δliq_t is computed as $\Delta liq_t = -(\Delta liq_t - \Delta liq_{t-1})$. Hence, a positive Δliq_t indicates that global liquidity has improved in this month. Brunnermeier, Nagel and Pedersen (2008) show that carry trade positions are unwound following decreases in liquidity.
6. ΔVIX_t: change in the CBOE VIX index, as in Brunnermeier, Nagel and Pedersen (2008).
7. $term_t$: the term premium averaged across the countries in the sample, based on Ang and Chen (2010), where they show that term premium predicts currency returns. The individual country term premium is the difference between the yield of a 10-year government bond and one-month interest rate (LIBOR or equivalent).
8. AFD_t : average forward discount across countries, based on Lustig, Roussanov, Verdelhan and Sloan (2012). Forward discount s computed as $\frac{S_t - F_t}{F_t}$, where S_t is the spot rate and F_t is the forward rate at the end of month $\mathbf{t}$, with the U.S. dollar as the home currency. As exchange rates are denoted as home currency per foreign currency unit (FCU), a negative (positive) AFD indicates that the foreign interest rate is lower (higher) than the U.S. dollar interest rate. Lustig, Roussanov, Verdelhan and Sloan (2012) document that AFD_t predicts U.S. dollar excess currency returns at long horizon.
9. ΔIP_t^{OECD}: percentage change in industrial production of the OECD countries, as a proxy for global economic growth, based on Lustig, Roussanov, Verdelhan and Sloan (2012). They find that IP growth predict carry trade profits at long horizon, after controlling for AFD_t .

The summary statistics and correlation matrix, the contemporaneous correlations among these variables, and with profits from the long leg and short leg of carry trades, respectively, and with the combined profits where I bet half a dollar on each leg are shown below:

Panel A. Summary statistics

	mean	S.D.	Skewness	Kurtosis	$\rho(-1)$
$\Delta\sigma_t^{equity}$	4.7E-05	0.443	2.08	17.26	**-0.24**
r_t^{world}	0.60	4.593	-0.64	1.55	**0.11**
r_t^{crb}	0.30	2.906	-1.69	14.65	**0.34**
Δliq_t	-3.7E-03	0.120	-1.47	19.08	**-0.12**
$\Delta\sigma_t^{fx}$	-2.7E-04	0.153	0.71	2.96	**-0.31**
ΔVIX_t	1.1E-02	5.007	1.82	14.63	-0.08
$term_t$	0.68	1.052	-0.30	-0.51	**0.97**
AFD_t	8.3E-04	0.002	0.20	-0.48	**0.86**
ΔIP_t^{OECD}	0.16	0.634	-2.19	10.91	**0.38**

First order autocorrections significant at 10% level are shown in bold fonts.

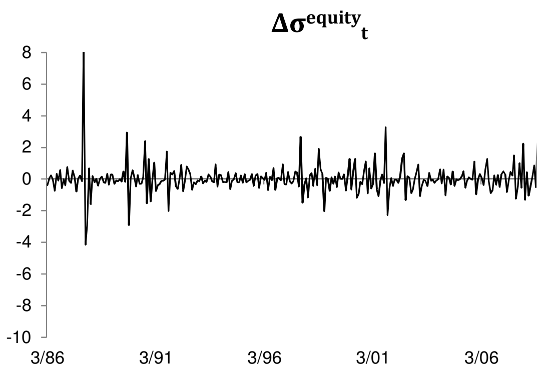
Panel B. correlation matrix

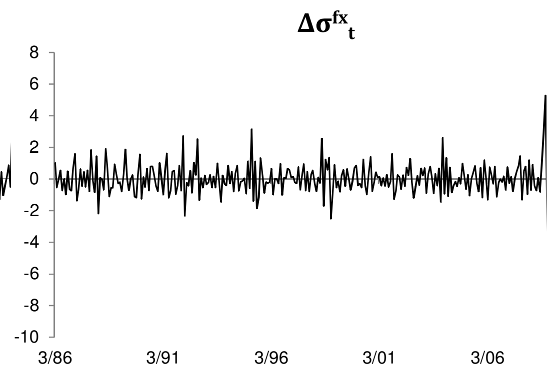
	$\boldsymbol{\Delta\sigma_t^{equity}}$	$\boldsymbol{r_t^{world}}$	$\boldsymbol{r_t^{crb}}$	$\boldsymbol{\Delta liq_t}$	$\boldsymbol{\Delta\sigma_t^{fx}}$	$\boldsymbol{\Delta VIX_t}$	$\boldsymbol{term_t}$	$\boldsymbol{AFD_t}$	$\boldsymbol{\Delta IP_t^{OECD}}$
$\boldsymbol{\Delta\sigma_t^{equity}}$	1.00	-0.40	-0.22	-0.20	0.46	0.63	-0.05	-0.02	0.08
$\boldsymbol{r_t^{world}}$		1.00	0.29	0.12	-0.24	-0.60	0.10	0.02	0.08
$\boldsymbol{r_t^{crb}}$			1.00	0.12	-0.21	-0.25	0.24	-0.02	0.31
$\boldsymbol{\Delta liq_t}$				1.00	-0.13	-0.19	0.19	0.00	-0.02
$\boldsymbol{\Delta\sigma_t^{fx}}$					1.00	0.27	-0.06	0.01	-0.02
$\boldsymbol{\Delta VIX_t}$						1.00	-0.07	-0.05	0.08
$\boldsymbol{term_t}$							1.00	-0.28	0.24
$\boldsymbol{AFD_t}$								1.00	-0.13
$\boldsymbol{\Delta IP_t^{OECD}}$									1.00

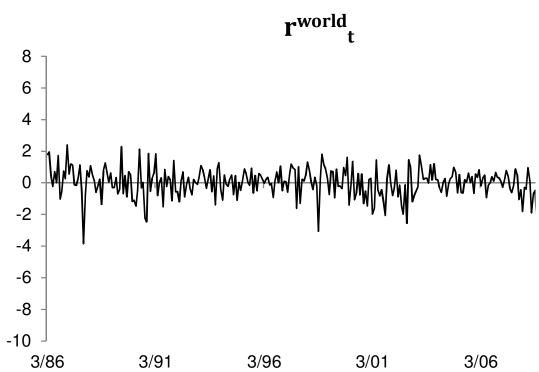
	short leg			long leg			Short+long		
Strategy	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
$\Delta\boldsymbol{\sigma}_t^{equity}$	-0.10	-0.09	-0.07	-0.15	-0.15	-0.15	-0.13	-0.14	-0.13
$\boldsymbol{r}_t^{world}$	-0.12	-0.14	-0.15	0.42	0.43	0.44	0.30	0.33	0.32
$\boldsymbol{r}_t^{crb}$	-0.03	-0.09	-0.10	0.33	0.39	0.41	0.25	0.28	0.28
$\Delta\boldsymbol{liq}_t$	-0.01	0.04	0.04	0.05	0.04	0.02	0.04	0.06	0.05
$\Delta\boldsymbol{\sigma}_t^{fx}$	-0.18	-0.11	-0.09	-0.13	-0.15	-0.18	-0.18	-0.17	-0.18
$\Delta\boldsymbol{VIX}_t$	-0.03	-0.07	-0.06	-0.26	-0.26	-0.26	-0.24	-0.28	-0.28
$\boldsymbol{term}_t$	0.02	0.02	0.02	0.10	0.11	0.12	0.10	0.12	0.13
$\boldsymbol{AFD}_t$	-0.11	-0.13	-0.13	0.07	0.08	0.07	0.00	-0.02	-0.03
$\Delta\boldsymbol{IP}_t^{OECD}$	0.09	0.06	0.06	0.17	0.18	0.16	0.22	0.21	0.19

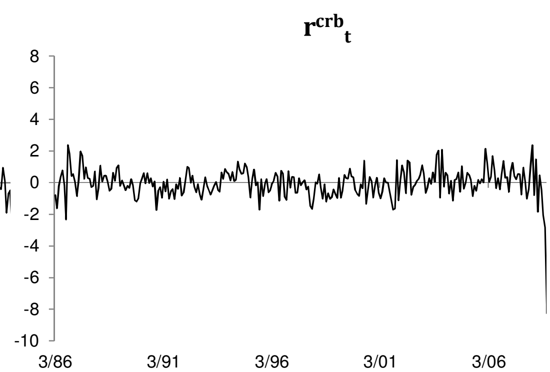
Appendix 3.C. Changes of predictors over time

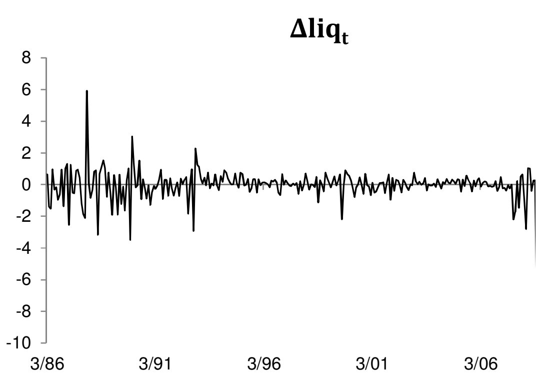
Standardized predictors with zero mean and unit variance are plotted over time. Appendix 3.A. contains the details of each predictor. Data are from Datastream and Global Financial Data.

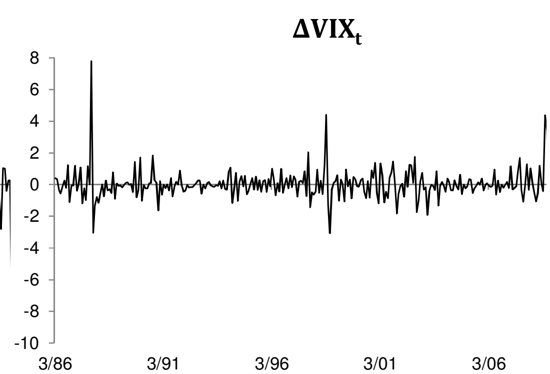


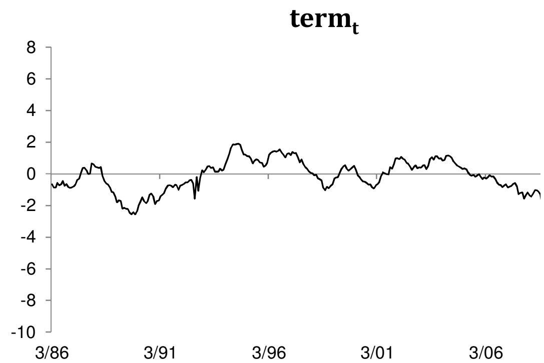




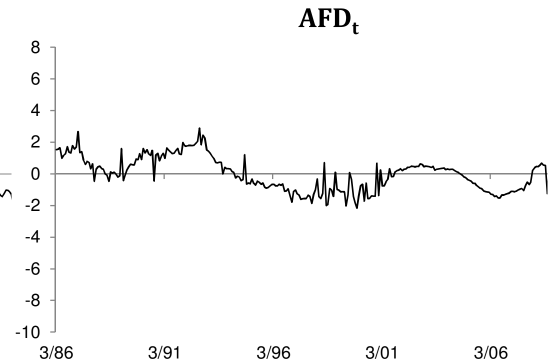




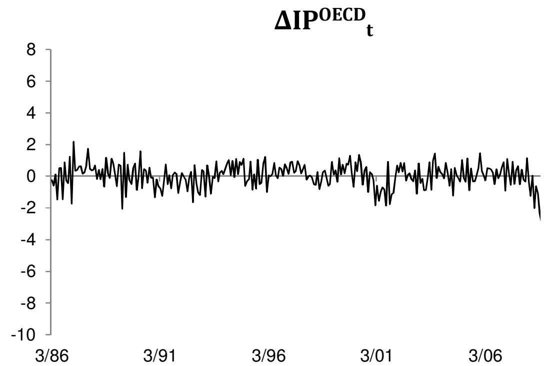




$term_t$
8
6
4
2
0
-2
-4
-6
-8
-10
3/86
3/91
3/96
3/01
3/06



AFD_t
8
6
4
2
0
-2
-4
-6
-8
-10
3/86
3/91
3/96
3/01
3/06



$\Delta IP^{OECD}{}_t$
8
6
4
2
0
-2
-4
-6
-8
-10
3/86
3/91
3/96
3/01
3/06

Appendix 3.D. Predictability in the currency component of carry trade profits

	Strategy	month t-1 beta1	t-values	adj. R2	month t-2 beta1	t-values	adj. R2	month t-3 beta1	t-values	adj. R2
Predictors for short leg profits										
chg. in equity	1	0.00	0.00	0.0%	-1.64	**-3.35***	0.0%	0.50	0.86	0.0%
volatility,	2	0.27	0.51	-0.7%	-1.46	**-4.12***	4.9%	0.62	1.29	-0.1%
	3	0.26	0.48	-0.5%	-1.51	**-4.35***	5.2%	0.61	1.27	0.4%
chg. in currency	1	0.95	0.66	-0.4%	-3.89	**-2.37***	3.1%	0.71	0.44	-0.5%
volatility,	2	1.20	1.14	-0.2%	-2.77	**-2.24***	1.9%	1.04	0.88	-0.3%
	3	0.94	0.91	-0.3%	-2.58	**-2.09**	1.7%	1.09	0.94	-0.2%
world equity	1	0.07	**1.67**	0.5%	0.12	**2.15***	2.7%	-0.01	-0.18	-0.6%
index return,	2	0.04	1.27	-0.1%	0.10	**2.39***	2.2%	-0.03	-0.67	-0.4%
	3	0.04	1.13	-0.2%	0.10	**2.31***	2.3%	-0.03	-0.75	-0.4%
Predictors for long-leg profits										
chg. in CRB	1	0.14	**1.87**	1.0%	0.05	0.51	-0.1%	0.30	**3.48***	5.7%
index,	2	0.13	**2.03**	2.0%	0.06	0.81	0.9%	0.26	**3.76***	6.8%
	3	0.12	**1.90**	2.4%	0.05	0.61	1.2%	0.21	**3.83***	5.5%
chg. in equity	1	-0.37	-0.62	0.0%	0.74	1.60	0.6%	-1.12	**-2.11**	1.7%
volatility,	2	-0.22	-0.34	0.7%	0.49	1.22	1.1%	-1.03	**-2.25***	2.7%
	3	-0.27	-0.42	1.2%	0.56	1.57	1.7%	-0.92	**-2.41***	3.0%

chg. in currency	1	-1.60	-0.92	0.2%	-0.75	-0.39	-0.2%	-3.19	**-1.76**	1.6%
volatility,	2	-1.73	-1.19	1.3%	-0.11	-0.07	0.6%	-3.06	**-1.99**	2.9%
	3	-1.75	-1.24	1.9%	0.06	0.048	0.9%	-2.35	**-1.85**	2.5%
Predictors for short/long strategy profits										
chg. in CRB	1	0.14	**2.18***	2.5%	0.16	**2.63***	3.2%	0.21	**2.58***	5.1%
index,	2	0.12	**2.35***	2.2%	0.12	**2.47***	2.4%	0.18	**2.41***	4.6%
	3	0.11	**2.21***	2.5%	0.10	**2.28***	2.5%	0.13	**2.57***	3.6%
chg. in equity	1	-0.19	-0.38	1.0%	-0.31	-0.68	1.1%	-0.78	-1.39	2.2%
volatility,	2	-0.05	-0.13	0.4%	-0.35	-0.89	0.8%	-0.70	-1.35	2.0%
	3	-0.11	-0.30	0.8%	-0.37	-1.08	1.4%	-0.55	-1.27	2.0%
chg. in currency	1	-0.30	-0.19	0.9%	-2.67	-1.59	2.8%	-2.97	**-1.91**	3.2%
volatility,	2	-0.83	-0.67	0.7%	-1.57	-1.10	1.4%	-2.43	**-1.77**	2.7%
	3	-0.93	-0.83	1.2%	-1.51	-1.31	1.9%	-1.70	-1.57	2.2%

Appendix 3.E. Predictability in the interest component of carry trade profit

		month $t-1$			month $t-2$			month $t-3$		
	Strategy	β_1	t-values	adj. R2	β_1	t-values	adj. R2	β_1	t-values	adj. R2
Predictors for short leg profits										
chg. in equity	1	0.03	0.81	36.7%	0.00	0.03	36.4%	-0.03	**-1.74**	36.7%
volatility,	2	0.01	0.31	44.5%	0.01	0.29	44.5%	-0.02	-1.49	44.6%
	3	0.00	0.05	44.6%	0.01	0.51	44.7%	-0.01	-1.20	44.7%
chg. in currency	1	-0.05	-0.58	36.5%	0.02	0.164	36.5%	0.04	0.37	36.5%
volatility,	2	-0.06	-1.15	44.8%	0.03	0.467	44.6%	0.00	0.00	44.5%
	3	-0.04	-0.84	44.8%	0.02	0.454	44.7%	-0.01	-0.1	44.6%
world equity	1	0.00	-0.39	36.5%	0.00	1.41	37.0%	0.00	**2.67***	37.1%
index return,	2	0.00	0.201	44.5%	0.00	1.14	44.9%	0.00	**2.10**	44.8%
	3	0.00	0.257	44.6%	0.00	0.95	44.9%	0.00	**1.84**	44.9%
Predictors for long-leg profits										
chg. in CRB	1	-0.01	-1.2	27.0%	0.00	-0.6	26.5%	0.00	0.26	26.0%
index,	2	0.00	-1.2	46.1%	0.00	-0.3	45.5%	0.00	0.43	45.0%
	3	0.00	-1.1	43.0%	0.00	-0.3	42.5%	0.00	0.32	42.0%
chg. in equity	1	0.01	0.30	26.7%	0.00	-0.0	26.4%	0.01	0.54	26.0%
volatility,	2	-0.01	-0.36	46.0%	0.01	0.57	45.5%	0.00	-0.20	44.9%
	3	0.00	-0.25	42.8%	0.01	0.31	42.5%	0.00	0.28	42.0%
chg. in currency	1	0.19	1.36	27.7%	-0.20	**-2.01**	27.5%	0.24	**2.20***	27.5%
volatility,	2	0.10	1.27	46.4%	-0.13	**-1.98**	46.3%	0.16	**2.50***	46.1%

	Strategy	month $t-1$ β_1	t-values	adj. R2	month $t-2$ β_1	t-values	adj. R2	month $t-3$ β_1	t-values	adj. R2
	3	0.10	1.36	43.4%	-0.13	**-2.09**	43.4%	0.15	**2.50***	43.3%
Predictors for short/long strategy profits										
chg. in CRB	1	-0.01	**-1.73**	28.3%	0.00	-0.4	27.7%	0.00	-1.04	27.7%
index,	2	0.00	-1.56	42.1%	0.00	-0.2	41.7%	0.00	-1.00	41.7%
	3	0.00	-1.29	43.4%	0.00	-0.1	43.0%	0.00	-0.93	43.0%
chg. in equity	1	0.03	1.03	28.1%	-0.01	-0.27	27.7%	0.00	-0.10	27.6%
volatility,	2	0.00	0.11	41.8%	0.01	0.456	41.7%	0.00	-0.30	41.5%
	3	0.00	-0.05	43.1%	0.01	0.418	43.1%	0.00	0.11	42.9%
chg. in currency	1	0.12	1.40	28.5%	-0.11	-1.31	28.2%	0.15	1.41	28.7%
volatility,	2	0.06	1.27	42.2%	-0.07	-1.57	42.2%	0.10	1.60	42.5%
	3	0.07	1.51	43.7%	-0.07	**-1.80**	43.7%	0.08	1.56	43.8%

Appendix 3.F. Including contemporaneous effects and control for serial correlations in predictors

These results are generated from based on equation (3) with additional controls for the contemporaneous effect and predictor variables lagged by fewer months than that used in (3). For example, when regressing carry trade profits in month t on predictor in month $t-3$, predictor in month t, $t-1$ and $t-2$ are all controlled for. Similar to the approach in Table 2, carry trade profit in month t-1 is also included as an explanatory variable. t-statistics significant at the 10% level or better are in bold.

		month $t-1$			month $t-2$			month $t-3$		
	Strategy	β_1	t	$\bar{R}^2$	β_1	t	$\bar{R}^2$	β_1	t	$\bar{R}^2$
Predictors for short leg profits										
chg. in equity	1	-0.13	-0.19	0.1%	-1.92	**-3.78**	6.7%	-0.11	-0.21	6.7%
volatility, $\Delta\sigma_{t-i}^{equity}$	2	0.17	0.30	-0.1%	-1.62	**-4.28**	6.1%	0.21	0.51	6.3%
	3	0.18	0.32	-0.4%	-1.66	**-4.37**	6.6%	0.19	0.47	6.7%
chg. in currency	1	-0.09	-0.06	1.9%	-4.61	**-2.85**	6.1%	-1.06	-0.68	6.0%
volatility, $\Delta\sigma_{t-i}^{FX}$	2	0.73	0.66	0.2%	-2.94	**-2.35**	2.4%	0.12	0.10	1.9%
	3	0.57	0.52	-0.1%	-2.77	**-2.21**	1.9%	0.23	0.18	1.4%
world equity	1	0.07	**1.80**	1.3%	0.11	**2.08**	3.9%	-0.01	-0.24	4.5%
index return,	2	0.05	1.52	1.5%	0.09	**2.33**	3.7%	-0.03	-0.79	4.5%
$\boldsymbol{r_{t-i}^{world}}$	3	0.05	1.40	1.6%	0.09	**2.27**	3.9%	-0.03	-0.90	4.8%
Predictors for long-leg profits										
chg. in CRB	1	0.00	-0.05	10.8%	-0.01	-0.17	10.9%	0.27	**2.83**	15.6%
index,	2	0.00	0.04	14.4%	0.01	0.09	14.5%	0.24	**2.87**	19.1%
$\boldsymbol{r_{t-i}^{CRB}}$	3	0.00	-0.07	16.6%	0.00	-0.06	16.8%	0.18	**2.99**	20.0%
chg. in equity	1	-0.67	-1.11	2.6%	0.45	0.76	2.5%	-1.18	**-2.12**	4.3%
volatility,	2	-0.52	-0.84	3.7%	0.23	0.46	3.5%	-1.13	**-2.28**	5.6%
$\Delta\sigma_{t-i}^{equity}$	3	-0.55	-0.90	4.3%	0.31	0.73	4.1%	-0.99	**-2.22**	6.1%
chg. in currency	1	-2.67	-1.50	2.7%	-2.20	-1.09	3.1%	-4.75	**-2.17**	6.6%
volatility,	2	-2.92	**-1.92**	5.1%	-1.53	-0.94	5.3%	-4.41	**-2.56**	9.2%
$\Delta\sigma_{t-i}^{FX}$	3	-3.00	**-2.02**	7.2%	-1.39	-0.97	7.3%	-3.55	**-2.29**	10.3%

	Strategy	β_1	t	$\bar{R}^2$	β_1	t	$\bar{R}^2$	β_1	t	$\bar{R}^2$
		month $t-1$			month $t-2$			month $t-3$		
Predictors for short/long strategy profits										
chg. in CRB	1	0.05	0.88	6.3%	0.12	**1.93**	7.5%	0.16	1.62	9.3%
index,	2	0.05	1.01	7.2%	0.08	1.53	8.0%	0.13	1.56	9.9%
$\boldsymbol{r_{t-i}^{CRB}}$	3	0.04	0.88	7.7%	0.07	1.51	8.4%	0.09	1.50	9.3%
chg. in equity	1	-0.42	-0.76	3.0%	-0.62	-1.05	3.4%	-1.12	**-2.11**	5.6%
volatility,	2	-0.27	-0.59	2.5%	-0.58	-1.20	3.2%	-1.00	**-2.04**	5.8%
$\Delta\sigma_{t-i}^{equity}$	3	-0.31	-0.76	2.8%	-0.61	-1.51	3.8%	-0.85	**-2.02**	6.0%
chg. in currency	1	-1.51	-0.98	5.0%	-3.91	**-2.21**	8.2%	-5.25	**-3.20**	14.0%
volatility,	2	-1.81	-1.45	4.3%	-2.70	**-1.84**	6.5%	-4.12	**-3.06**	11.7%
$\Delta\sigma_{t-i}^{FX}$	3	-1.92	**-1.70**	5.8%	-2.70	**-2.26**	8.4%	-3.31	**-2.97**	12.3%

Appendix 3.G. Additional out-of-sample performance of prediction model

This table reports out-of-sample R^2's (Goyal and Welch , 2008) for predicting carry trade profits with single predictors and MSPE-adjusted one-sided p-values (Clark and West, 2007), using regression specified in equation (3). Details of statistical estimations can be found in Table 4. In order to facilitate comparison with results in Bakshi and Panayotov (2012), I also use three-month changes in commodity prices, three month changes in currency volatility and three month changes in equity volatility (normalized to monthly) to predict long/short profits.

Results from predicting carry trade profits using monthly changes in a single predictor variable are reported in Panel A, B, C and D. Out-of-sample prediction results using three-month changes in a single variable are reported in Panel D. Out-of-sample results using three-month changes in two variables are reported in Panel E.

Panel A. predicting short leg profits in month t

		Predictors	
$OoS\ R^2$ (%)	$\boldsymbol{r_{t-2}^{world}}$	$\Delta\boldsymbol{\sigma_{t-2}^{FX}}$	$\Delta\boldsymbol{\sigma_{t-2}^{equity}}$
Strategy			
1	4.7	5.0	6.2
2	3.4	3.4	5.4
3	3.3	3.1	5.5
MSPE-adjusted one-sided p-values			
1	0.07	0.07	0.11
2	0.07	0.05	0.10
3	0.07	0.05	0.11

Panel B. predicting long-leg profits in month t

		Predictors	
$OoS\ R^2$ (%)	$\boldsymbol{r_{t-3}^{CRB}}$	$\Delta\boldsymbol{\sigma_{t-3}^{equity}}$	$\Delta\boldsymbol{\sigma_{t-3}^{FX}}$
Strategy			
1	6.6	1.6	1.6
2	6.9	1.9	1.8
3	5.5	1.6	1.0
MSPE-adjusted one-sided p-values			
1	0.05	0.05	0.08
2	0.04	0.05	0.11
3	0.04	0.15	0.22

Panel C. predicting long/short profits in month t with a single model

		Predictors	
$OoS\ R^2$ (%)	$\boldsymbol{r_{t-3}^{CRB}}$	$\Delta\boldsymbol{\sigma_{t-3}^{equity}}$	$\Delta\boldsymbol{\sigma_{t-3}^{FX}}$
Strategy			
1	7.2	1.9	3.2
2	5.2	1.9	2.3
3	4.2	1.6	1.5
MSPE-adjusted one-sided p-values			
1	0.03	0.03	0.04
2	0.04	0.04	0.05
3	0.02	0.05	0.07

Panel D. predicting long/short profits in month t with a different model for each leg (Strategy 1)

$OoS\ R^2$ (%)

	Long-leg predictors		
Short leg predictors	$\boldsymbol{r_{t-3}^{CRB}}$	$\Delta\boldsymbol{\sigma_{t-3}^{equity}}$	$\Delta\boldsymbol{\sigma_{t-3}^{FX}}$
$\boldsymbol{r_{t-2}^{world}}$	12.7	4.5	4.1
$\Delta\boldsymbol{\sigma_{t-2}^{FX}}$	13.3	4.7	4.5
$\Delta\boldsymbol{\sigma_{t-2}^{equity}}$	13.0	4.5	4.2

MSPE-adjusted one-sided p-values

	Long-leg predictors		
Short leg predictors	$\boldsymbol{r_{t-3}^{CRB}}$	$\Delta\boldsymbol{\sigma_{t-3}^{equity}}$	$\Delta\boldsymbol{\sigma_{t-3}^{FX}}$
$\boldsymbol{r_{t-2}^{world}}$	0.04	0.00	0.01
$\Delta\boldsymbol{\sigma_{t-2}^{FX}}$	0.04	0.00	0.01
$\Delta\boldsymbol{\sigma_{t-2}^{equity}}$	0.04	0.00	0.01

Panel E. predicting long/short profits in month t with three-month changes in predictor variable

$OoS\ R^2$ (%)

	Predictors		
Strategy	$\boldsymbol{(\frac{CRB_{t-3}}{CRB_{t-1}}-1)^{1/3}-1}$	$\boldsymbol{\frac{\sigma_{t-3}^{equity}-\sigma_{t-1}^{equity}}{3}}$	$\boldsymbol{\frac{\sigma_{t-3}^{FX}-\sigma_{t-1}^{FX}}{3}}$
1	9.4	3.8	10.1
2	7.3	3.7	8.3
3	6.7	4.2	7.7
MSPE-adjusted one-sided p-values			
1	0.02	0.05	0.01
2	0.02	0.05	0.01
3	0.02	0.05	0.01

Panel F. predicting long/short profits in month t with three-month changes in two predictor variables

$OoS\ R^2$ (%)

	Predictors		
Strategy	$\boldsymbol{(\frac{CRB_{t-3}}{CRB_{t-1}}-1)^{1/3}-1}$ & $\boldsymbol{\frac{\sigma_{t-3}^{equity}-\sigma_{t-1}^{equity}}{3}}$	$\boldsymbol{(\frac{CRB_{t-3}}{CRB_{t-1}}-1)^{1/3}-1}$ & $\boldsymbol{\frac{\sigma_{t-3}^{FX}-\sigma_{t-1}^{FX}}{3}}$	$\boldsymbol{\frac{\sigma_{t-3}^{equity}-\sigma_{t-1}^{equity}}{3}}$ & $\boldsymbol{\frac{\sigma_{t-3}^{FX}-\sigma_{t-1}^{FX}}{3}}$
1	10.1	13.0	9.6
2	8.2	10.4	7.8
3	8.2	9.7	7.6
MSPE-adjusted one-sided p-values			
1	0.02	0.01	0.01
2	0.02	0.01	0.01
3	0.02	0.01	0.01

Appendix 3.H. Additional economic significance results– profits from market-timing strategies

This table reports the annual mean, Sharpe ratio and skewness of monthly profits from market-timing strategies conditional on predicted carry trade. I use one predictor in each model to predictor carry trade profits. Using the market-timing carry trade strategy, one goes ahead with the carry trade if the predicted profits are positive and does nothing otherwise. Profits from market-timing strategies based on these predictions are reported in Panel A to D.

In order to facilitate comparison with results in Bakshi and Panayotov (2012), I also use three-month changes in commodity prices, three-month changes in currency volatility and three-month changes in equity volatility (normalized to monthly) to predict long/short profits. Profits from market-timing strategies based on the predictions using a single predictor are reported in Panel E. Profits from market-timing strategies based on the predictions using two predictors are reported in Panel E.

The sample period is from January 1985 to December 2011. Table 5 contains details on construction of profits from market-timing strategies.

Panel A. short-leg profits conditioned on model prediction

	Mean (annual)				Sharpe Ratio (annual)				Skewness (monthly)			
Strategy	Simple	r_{t-2}^{world}	$\Delta\sigma_{t-2}^{FX}$	$\Delta\sigma_{t-2}^{equity}$	Simple	r_{t-2}^{world}	$\Delta\sigma_{t-2}^{FX}$	$\Delta\sigma_{t-2}^{equity}$	Simple	r_{t-2}^{world}	$\Delta\sigma_{t-2}^{FX}$	$\Delta\sigma_{t-2}^{equity}$
1	-1.74	1.47	0.87	-1.27	-0.20	0.26	0.14	-0.19	-1.08	0.81	0.81	0.24
2	-1.45	0.14	0.08	-0.54	-0.19	0.02	0.01	-0.08	-0.38	0.27	0.31	0.25
3	-1.93	-0.23	-0.11	-0.69	-0.25	-0.04	-0.02	-0.11	-0.34	0.28	0.31	0.25
1		**[0.05]**	**[0.06]**	[0.39]		**[0.03]**	**[0.06]**	[0.49]		**[0.01]**	**[0.00]**	**[0.04]**
2		[0.13]	**[0.10]**	[0.22]		[0.15]	[0.11]	[0.25]		[0.11]	**[0.07]**	**[0.08]**
3		[0.11]	**[0.06]**	[0.14]		[0.14]	**[0.08]**	[0.17]		[0.15]	**[0.09]**	[0.12]

Panel B. long-leg profits conditioned on model prediction

Strategy	Mean (annual) simple	r^{CRB}_{t-3}	$\Delta\sigma^{equity}_{t-3}$	$\Delta\sigma^{FX}_{t-3}$	Sharpe Ratio (annual) simple	r^{CRB}_{t-3}	$\Delta\sigma^{equity}_{t-3}$	$\Delta\sigma^{FX}_{t-3}$	Skewness (monthly) simple	r^{CRB}_{t-3}	$\Delta\sigma^{equity}_{t-3}$	$\Delta\sigma^{FX}_{t-3}$
1	9.08	9.48	8.82	8.46	0.68	0.80	0.67	0.69	-0.60	-0.48	-0.62	-0.41
2	7.47	8.62	7.80	7.14	0.60	0.81	0.63	0.63	-0.52	-0.40	-0.54	-0.53
3	5.80	7.16	6.16	5.39	0.52	0.75	0.57	0.52	-0.74	-0.82	-0.76	-0.95
1		[0.42]	[0.67]	[0.72]		[0.22]	[0.64]	[0.49]		[0.37]	[0.85]	[0.18]
2		[0.28]	[0.27]	[0.58]		**[0.10]**	[0.26]	[0.36]		[0.34]	[0.63]	[0.51]
3		[0.23]	[0.36]	[0.66]		**[0.08]**	[0.28]	[0.46]		[0.54]	[0.48]	[0.85]

Panel C. Long/short profits conditioned on predictions from a single model

Strategy	Mean (annual) simple	r^{CRB}_{t-3}	$\Delta\sigma^{equity}_{t-3}$	$\Delta\sigma^{FX}_{t-3}$	Sharpe Ratio (annual) Simple	r^{CRB}_{t-3}	$\Delta\sigma^{equity}_{t-3}$	$\Delta\sigma^{FX}_{t-3}$	Skewness (monthly) simple	r^{CRB}_{t-3}	$\Delta\sigma^{equity}_{t-3}$	$\Delta\sigma^{FX}_{t-3}$
1	5.76	7.45	6.04	5.79	0.53	0.82	0.56	0.60	-0.56	-0.07	-0.58	-0.16
2	4.99	5.51	5.52	3.62	0.50	0.64	0.56	0.39	-0.03	0.09	-0.05	-0.37
3	3.54	4.16	4.14	2.52	0.40	0.52	0.47	0.30	0.01	-0.10	0.00	-0.24
1		[0.19]	[0.24]	[0.50]		**[0.09]**	[0.24]	[0.36]		[0.18]	[0.74]	[0.26]
2		[0.38]	[0.17]	[0.91]		[0.23]	[0.17]	[0.89]		[0.41]	[0.84]	[0.87]
3		[0.34]	[0.17]	[0.88]		[0.23]	[0.17]	[0.85]		[0.61]	[0.76]	[0.90]

Panel D. Long/short profits where profits from each leg are conditioned on predictions from a different models

Strategy 1	Mean (annual)			Sharpe ratio (annual)			Skewness (monthly)		
	Long-leg predictors			Long-leg predictors			Long-leg predictors		
Short leg predictors	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$
r_{t-2}^{world}	8.04	7.41	7.03	0.92	0.72	0.77	0.09	-0.50	0.11
$\Delta\sigma_{t-2}^{FX}$	7.75	7.12	6.73	0.88	0.69	0.73	0.08	-0.49	0.10
$\Delta\sigma_{t-2}^{equity}$	6.68	6.05	5.66	0.73	0.57	0.60	-0.14	-0.56	-0.08
r_{t-2}^{world}	[0.14]	**[0.03]**	[0.21]	**[0.04]**	**[0.01]**	**[0.08]**	[0.11]	[0.39]	**[0.04]**
$\Delta\sigma_{t-2}^{FX}$	[0.17]	**[0.04]**	[0.27]	**[0.06]**	**[0.02]**	[0.12]	[0.12]	[0.38]	**[0.05]**
$\Delta\sigma_{t-2}^{equity}$	[0.35]	[0.36]	[0.53]	[0.21]	[0.29]	[0.37]	[0.24]	[0.46]	[0.12]
r_{t-2}^{world}	{0.33}	**{0.05}**	**{0.07}**	{0.30}	**{0.02}**	**{0.04}**	{0.35}	{0.35}	**{0.09}**
$\Delta\sigma_{t-2}^{FX}$	{0.39}	**{0.07}**	**{0.10}**	{0.35}	**{0.04}**	**{0.06}**	{0.35}	{0.34}	{0.11}
$\Delta\sigma_{t-2}^{equity}$	{0.72}	{0.47}	{0.55}	{0.67}	{0.41}	{0.48}	{0.61}	{0.38}	{0.15}

Panel E. Long/short profits conditioned on predictions from on variable: three-month changes in predictor variable lagged by one month

	Mean (annual)				Sharpe Ratio (annual)				Skewness (monthly)			
Strategy	Simple	$(\frac{CRB_{t-3}}{CRB_{t-1}} - 1)^{1/3} - 1$	$\frac{\sigma_{t-3}^{equity} -}{3}$	$\frac{\sigma_{t-3}^{FX} - \sigma_{t-1}^{FX}}{3}$	Simple	$(\frac{CRB_{t-3}}{CRB_{t-1}} - 1)^{1/3} - 1$	$\frac{\sigma_{t-3}^{equity} - \sigma_{t}^{e}}{3}$	$\frac{\sigma_{t-3}^{FX} - \sigma_{t-1}^{FX}}{3}$	Simple	$(\frac{CRB_{t-3}}{CRB_{t-1}} - 1)^{1/3} - 1$	$\frac{\sigma_{t-3}^{equity} - \sigma_{t-1}^{equ}}{3}$	$\frac{\sigma_{t-3}^{FX} - \sigma_{t-1}^{FX}}{3}$
1	5.76	8.26	6.07	8.17	0.53	1.02	0.63	1.01	-0.56	0.57	-0.72	0.85
2	4.99	6.91	5.46	6.07	0.50	0.90	0.62	0.72	-0.03	1.24	0.20	0.60
3	3.54	5.38	3.92	4.47	0.40	0.77	0.54	0.64	0.01	0.85	0.48	0.94

Panel F. Long/short profits conditioned on predictions from two variables: three-month changes in predictor variable lagged by one month

Strategy	Mean (annual)				Sharpe Ratio (annual)				Skewness (monthly)			
	Simple	$(\frac{CRB_{t-3}}{CRB_{t-1}} - 1)^{1/3} - 1$ & $\frac{\sigma^{equity}_{t-3} - \sigma^{equity}_{t-1}}{3}$	$(\frac{CRB_{t-3}}{CRB_{t-1}} - 1)^{1/3} - 1$ & $\frac{\sigma^{FX}_{t-3} - \sigma^{FX}_{t-1}}{3}$	$\frac{\sigma^{equity}_{t-3} - \sigma^{e}_{t}}{3}$ & $\frac{\sigma^{FX}_{t-3} - \sigma^{FX}_{t-1}}{3}$	Simple	$(\frac{CRB_{t-3}}{CRB_{t-1}} - 1)^{1/3} - 1$ & $\frac{\sigma^{equity}_{t-3} - \sigma^{equity}_{t-1}}{3}$	$(\frac{CRB_{t-3}}{CRB_{t-1}} - 1)^{1/3} - 1$ & $\frac{\sigma^{FX}_{t-3} - \sigma^{FX}_{t-1}}{3}$	$\frac{\sigma^{equity}_{t-3} - \sigma^{equit}_{t-1}}{3}$ & $\frac{\sigma^{FX}_{t-3} - \sigma^{FX}_{t-1}}{3}$	Simple	$(\frac{CRB_{t-3}}{CRB_{t-1}} - 1)^{1/3} - 1$ & $\frac{\sigma^{equity}_{t-3} - \sigma^{equity}_{t-1}}{3}$	$(\frac{CRB_{t-3}}{CRB_{t-1}} - 1)^{1/3} - 1$ & $\frac{\sigma^{FX}_{t-3} - \sigma^{FX}_{t-1}}{3}$	$\frac{\sigma^{equity}_{t-3} - \sigma^{e}_{t}}{3}$ & $\frac{\sigma^{FX}_{t-3} - \sigma^{FX}_{t-1}}{3}$
1	5.76	7.89	6.81	7.53	0.53	0.98	0.85	0.96	-0.56	0.60	0.71	0.83
2	4.99	6.86	6.29	6.64	0.50	0.89	0.82	0.83	-0.03	1.25	1.32	1.23
3	3.54	5.01	4.12	4.49	0.40	0.72	0.60	0.64	0.01	0.89	1.01	0.94

Appendix 3.I. In sample performance of all predictors – single predictor

This table reports coefficient estimates from regressions: $\overline{P}_t^{k_l} = \boldsymbol{\alpha} + \boldsymbol{\beta_1}\,\boldsymbol{Z_{t-i}} + \boldsymbol{\beta_2}\,\overline{P}_{t-1}^{k_l} + \boldsymbol{\mu_t}$ $(i = 1 \cdots 3, k = 1 \cdots 3,\ l = short, long, long/short)$, where $\boldsymbol{Z_{t-i}}$ is a single predictor.

strategy	$\boldsymbol{\sigma_{t-1}^{Equity}}$	t	p	$\overline{\boldsymbol{R^2}}$	$\boldsymbol{\sigma_{t-2}^{Equity}}$	t	p	$\overline{\boldsymbol{R^2}}$	$\boldsymbol{\sigma_{t-3}^{Equity}}$	t	p	$\overline{\boldsymbol{R^2}}$
combined profit												
1	-0.16	-0.34	0.74	0.6%	-0.31	-0.67	0.50	0.8%	-0.78	-1.40	0.16	1.9%
2	-0.05	-0.13	0.89	0.2%	-0.34	-0.86	0.39	0.6%	-0.70	-1.37	0.17	1.9%
3	-0.12	-0.31	0.75	0.6%	-0.37	-1.08	0.28	1.1%	-0.55	-1.27	0.21	1.8%
short leg profit												
1	0.05	0.08	0.94	-0.6%	-1.61	**-3.28**	**0.00**	4.7%	0.48	0.83	0.41	-0.2%
2	0.29	0.57	0.57	-0.4%	-1.44	**-4.03**	**0.00**	5.0%	0.62	1.30	0.19	0.4%
3	0.27	0.52	0.60	-0.4%	-1.49	**-4.29**	**0.00**	5.8%	0.62	1.29	0.20	0.5%
long-leg profit												
1	-0.35	-0.59	0.56	0.0%	0.75	1.63	0.10	0.7%	-1.11	**-2.11**	**0.04**	1.7%
2	-0.22	-0.34	0.73	0.9%	0.50	1.26	0.21	1.2%	-1.03	**-2.26**	**0.02**	2.9%
3	-0.27	-0.43	0.67	1.3%	0.57	1.60	0.11	1.9%	-0.92	**-2.41**	**0.02**	3.1%

strategy	σ^{FX}_{t-1}	t	p	$\overline{R^2}$	σ^{FX}_{t-2}	t	p	$\overline{R^2}$	σ^{FX}_{t-3}	t	p	$\overline{R^2}$
combined profit												
1	-0.20	-0.14	0.89	0.6%	-2.72	-1.63	0.10	2.5%	-2.87	**-1.84**	**0.07**	2.7%
2	-0.78	-0.64	0.52	0.4%	-1.61	-1.13	0.26	1.2%	-2.36	**-1.73**	**0.08**	2.4%
3	-0.88	-0.80	0.43	0.9%	-1.56	-1.36	0.17	1.7%	-1.64	-1.52	0.13	1.9%
short-leg profit												
1	0.98	0.69	0.49	-0.4%	-3.84	**-2.35**	**0.02**	2.9%	0.76	0.49	0.62	-0.5%
2	1.22	1.17	0.24	-0.2%	-2.74	**-2.22**	**0.03**	1.8%	1.08	0.93	0.35	-0.2%
3	0.96	0.94	0.35	-0.3%	-2.55	**-2.08**	**0.04**	1.6%	1.12	0.98	0.33	-0.2%
long-leg profit												
1	-1.42	-0.83	0.40	0.2%	-0.87	-0.46	0.65	-0.1%	-3.00	-1.65	0.10	1.4%
2	-1.63	-1.14	0.25	1.4%	-0.19	-0.12	0.90	0.7%	-2.95	**-1.92**	**0.06**	2.8%
3	-1.65	-1.19	0.24	1.9%	-0.01	-0.01	0.99	1.1%	-2.25	**-1.76**	**0.08**	2.5%
strategy	r^{world}_{t-1}	t	p	$\overline{R^2}$	r^{world}_{t-2}	t	p	$\overline{R^2}$	r^{world}_{t-3}	t	p	$\overline{R^2}$
combined profit												
1	0.02	0.45	0.65	0.7%	0.09	**1.99**	**0.05**	2.5%	0.01	0.16	0.87	0.6%
2	0.00	0.13	0.90	0.2%	0.07	**2.02**	**0.04**	2.1%	0.01	0.14	0.89	0.3%
3	0.00	-0.04	0.97	0.6%	0.06	**1.89**	**0.06**	2.3%	0.00	-0.01	1.00	0.6%
short-leg profit												
1	0.07	1.59	0.11	0.3%	0.12	**2.16**	**0.03**	2.7%	0.00	-0.07	0.95	-0.6%
2	0.04	1.25	0.21	-0.1%	0.10	**2.41**	**0.02**	2.3%	-0.02	-0.60	0.55	-0.5%
3	0.04	1.12	0.26	-0.2%	0.10	**2.34**	**0.02**	2.3%	-0.03	-0.70	0.49	-0.4%
long-leg profit												
1	0.00	0.00	1.00	-0.2%	0.02	0.45	0.65	-0.1%	0.00	0.07	0.95	-0.3%
2	-0.03	-0.61	0.54	0.9%	0.03	0.68	0.50	0.9%	0.01	0.11	0.91	0.6%
3	-0.04	-0.82	0.41	1.5%	0.02	0.38	0.71	1.1%	0.01	0.12	0.90	1.0%

strategy	ΔVIX_{t-1}	t	p	$\overline{R^2}$	ΔVIX_{t-2}	t	p	$\overline{R^2}$	ΔVIX_{t-3}	t	p	$\overline{R^2}$
combined profit												
1	0.03	0.52	0.60	0.8%	-0.08	**-2.02**	**0.04**	2.4%	-0.02	-0.51	0.61	0.7%
2	0.04	1.02	0.31	1.0%	-0.08	**-2.53**	**0.01**	2.7%	-0.02	-0.54	0.59	0.5%
3	0.04	1.06	0.29	1.2%	-0.08	**-2.66**	**0.01**	3.5%	-0.02	-0.42	0.68	0.8%
short-leg profit												
1	-0.04	-1.03	0.30	-0.1%	-0.12	**-1.98**	**0.05**	2.9%	0.01	0.19	0.85	-0.6%
2	-0.01	-0.33	0.74	-0.6%	-0.09	**-2.41**	**0.02**	2.4%	0.03	0.69	0.49	-0.2%
3	0.00	-0.12	0.90	-0.6%	-0.10	**-2.70**	**0.01**	3.4%	0.03	0.63	0.53	-0.3%
long-leg profit												
1	0.05	0.77	0.44	0.3%	-0.01	-0.29	0.77	-0.2%	-0.03	-0.57	0.57	-0.1%
2	0.06	1.07	0.29	1.7%	-0.02	-0.69	0.49	0.9%	-0.04	-0.89	0.37	1.0%
3	0.05	0.89	0.38	1.8%	-0.01	-0.39	0.70	1.1%	-0.03	-0.90	0.37	1.3%
strategy	r_{t-1}^{CRB}	t	p	$\overline{R^2}$	r_{t-2}^{CRB}	t	p	$\overline{R^2}$	r_{t-3}^{CRB}	t	p	$\overline{R^2}$
combined profit												
1	0.13	**2.05**	**0.04**	2.1%	0.15	**2.58**	**0.01**	2.8%	0.21	**2.52**	**0.01**	4.7%
2	0.12	**2.27**	**0.02**	1.9%	0.12	**2.42**	**0.02**	2.1%	0.17	**2.37**	**0.02**	4.3%
3	0.11	**2.15**	**0.03**	2.2%	0.10	**2.25**	**0.03**	2.3%	0.13	**2.52**	**0.01**	3.3%
short-leg profit												
1	0.05	0.72	0.47	-0.5%	0.16	1.56	0.12	1.7%	-0.06	-0.84	0.40	-0.4%
2	0.01	0.26	0.80	-0.6%	0.08	1.00	0.32	0.1%	-0.08	-1.50	0.14	0.2%
3	0.00	0.02	0.99	-0.6%	0.07	0.89	0.38	0.0%	-0.08	-1.47	0.14	0.2%
long-leg profit												
1	0.13	**1.73**	**0.09**	0.9%	0.05	0.47	0.64	-0.1%	0.30	**3.46**	**0.00**	5.7%
2	0.13	**1.92**	**0.06**	2.0%	0.06	0.77	0.44	1.0%	0.26	**3.76**	**0.00**	6.8%
3	0.12	**1.81**	**0.07**	2.4%	0.05	0.59	0.56	1.3%	0.21	**3.82**	**0.00**	5.6%

strategy combined profit	Δliq_{t-1}	t	p	$\overline{R^2}$	Δliq_{t-2}	t	p	$\overline{R^2}$	Δliq_{t-3}	t	p	$\overline{R^2}$
1	1.13	0.48	0.63	0.8%	2.09	1.22	0.22	1.3%	0.65	0.41	0.68	0.6%
2	0.68	0.43	0.67	0.3%	1.35	0.86	0.39	0.7%	1.43	1.09	0.28	0.7%
3	1.12	0.78	0.44	0.9%	1.89	1.44	0.15	1.6%	0.89	0.86	0.39	0.9%
short-leg profit												
1	1.33	0.60	0.55	-0.4%	-0.36	-0.23	0.82	-0.6%	0.87	0.28	0.78	-0.5%
2	-0.26	-0.15	0.88	-0.6%	-0.60	-0.45	0.65	-0.6%	0.88	0.39	0.70	-0.5%
3	-0.07	-0.04	0.97	-0.6%	-0.47	-0.35	0.72	-0.6%	0.87	0.39	0.70	-0.4%
long-leg profit												
1	1.80	0.60	0.55	0.2%	2.74	1.43	0.15	0.7%	-0.11	-0.05	0.96	-0.3%
2	2.05	0.77	0.44	1.4%	1.64	1.00	0.32	1.1%	0.96	0.58	0.56	0.8%
3	2.54	0.92	0.36	2.3%	2.18	1.57	0.12	1.9%	0.15	0.10	0.92	1.0%
strategy combined profit	$term_{t-1}$	t	p	$\overline{R^2}$	$term_{t-2}$	t	p	$\overline{R^2}$	$term_{t-3}$	t	p	$\overline{R^2}$
1	0.26	**1.72**	**0.09**	1.4%	0.27	**1.70**	**0.09**	1.5%	0.22	1.46	0.14	1.2%
2	0.25	**2.04**	**0.04**	1.3%	0.22	**1.81**	**0.07**	1.1%	0.20	1.60	0.11	1.0%
3	0.25	**2.13**	**0.03**	1.9%	0.21	**1.89**	**0.06**	1.6%	0.17	1.49	0.14	1.3%
short-leg profit												
1	0.08	0.44	0.66	-0.6%	0.03	0.16	0.87	-0.6%	0.05	0.27	0.79	-0.6%
2	0.02	0.11	0.91	-0.6%	-0.02	-0.15	0.88	-0.6%	-0.01	-0.03	0.97	-0.6%
3	0.03	0.18	0.86	-0.6%	-0.01	-0.09	0.93	-0.6%	0.00	-0.03	0.97	-0.6%
long-leg profit												
1	0.34	**1.84**	**0.07**	0.8%	0.38	**2.04**	**0.04**	1.0%	0.30	**1.67**	**0.10**	0.6%
2	0.31	**1.92**	**0.06**	1.9%	0.30	**1.90**	**0.06**	1.7%	0.27	**1.71**	**0.09**	1.5%
3	0.31	**2.05**	**0.04**	2.5%	0.29	**2.06**	**0.04**	2.2%	0.24	**1.70**	**0.09**	1.8%

strategy combined profit	AFP_{t-1}	t	p	$\overline{\boldsymbol{R^2}}$	AFP_{t-2}	t	p	$\overline{\boldsymbol{R^2}}$	AFP_{t-3}	t	p	$\overline{\boldsymbol{R^2}}$
1	0.10	0.09	0.93	0.6%	-0.07	-0.06	0.96	0.6%	0.08	0.06	0.95	0.6%
2	-0.27	-0.31	0.76	0.2%	-0.17	-0.18	0.85	0.3%	-0.12	-0.13	0.89	0.3%
3	-0.47	-0.54	0.59	0.7%	-0.36	-0.44	0.66	0.7%	-0.26	-0.31	0.76	0.7%
short-leg profit												
1	-1.21	-1.17	0.24	-0.2%	-0.87	-0.74	0.46	-0.4%	-0.26	-0.20	0.84	-0.6%
2	-1.67	**-1.90**	**0.06**	0.4%	-1.16	-1.24	0.22	-0.1%	-0.60	-0.62	0.54	-0.5%
3	-1.55	**-1.78**	**0.08**	0.3%	-1.30	-1.45	0.15	0.0%	-0.66	-0.72	0.47	-0.4%
long-leg profit												
1	1.45	1.10	0.27	0.3%	0.51	0.35	0.72	-0.1%	0.17	0.14	0.89	-0.3%
2	1.08	0.98	0.33	1.1%	0.59	0.54	0.59	0.8%	0.13	0.12	0.90	0.6%
3	0.69	0.66	0.51	1.3%	0.41	0.42	0.68	1.1%	-0.03	-0.03	0.98	0.9%
strategy combined profit	ΔIP_{t-1}^{OECD}	t	p	$\overline{\boldsymbol{R^2}}$	ΔIP_{t-2}^{OECD}	t	p	$\overline{\boldsymbol{R^2}}$	ΔIP_{t-3}^{OECD}	t	p	$\overline{\boldsymbol{R^2}}$
1	0.42	0.88	0.38	1.3%	0.47	1.04	0.30	1.6%	-0.08	-0.19	0.85	0.6%
2	0.30	0.72	0.47	0.8%	0.30	0.68	0.50	0.8%	-0.18	-0.42	0.67	0.5%
3	0.19	0.60	0.55	0.8%	0.29	0.85	0.40	1.3%	-0.15	-0.43	0.67	0.8%
short-leg profit												
1	0.22	0.55	0.59	-0.4%	0.20	0.72	0.47	-0.5%	0.08	0.26	0.79	-0.6%
2	0.02	0.06	0.95	-0.6%	0.05	0.22	0.83	-0.6%	0.02	0.10	0.92	-0.6%
3	0.00	0.00	1.00	-0.6%	-0.02	-0.10	0.92	-0.6%	0.05	0.21	0.84	-0.6%
long-leg profit												
1	0.51	0.90	0.37	0.7%	0.49	0.99	0.32	0.6%	-0.02	-0.04	0.97	-0.3%
2	0.49	1.00	0.32	1.7%	0.38	0.78	0.43	1.3%	-0.09	-0.19	0.85	0.6%
3	0.33	0.81	0.42	1.7%	0.44	1.12	0.26	2.1%	-0.09	-0.23	0.82	1.0%

Appendix 3.J. Out-of-sample performance of all predictors – single predictor

This table reports out-of-sample R^2's (Goyal and Welch , 2008) for predicting carry trade profits with single predictors and MSPE-adjusted one-sided p-values (Clark and West, 2007), using regression specified in equation (3). Details of statistical estimations can be found in Table 5.

Predicting profits from short leg of carry trade

Strategy K	r_{t-2}^{world}	r_{t-2}^{CRB}	$\Delta\sigma_{t-2}^{equity}$	$\Delta\sigma_{t-2}^{FX}$	Δliq_{t-2}	ΔVIX_{t-2}	$term_{t-2}$	AFD_{t-2}	ΔIP_{t-2}^{OECD}
$OoS\ R^2$ (%)									
1	4.29	2.04	8.17	3.34	-1.05	-0.07	-0.55	-0.12	-1.19
2	4.09	-1.93	8.43	2.53	-0.41	1.36	-0.54	-0.19	-1.49
3	3.63	-2.67	8.71	2.72	-0.46	1.18	-0.59	-0.06	-1.39
one-sided p-values									
1	0.06	0.14	0.03	0.13	0.22	0.13	0.34	0.39	0.24
2	0.03	0.19	0.01	0.11	0.42	0.07	0.39	0.34	0.22
3	0.05	0.19	0.02	0.11	0.43	0.06	0.40	0.24	0.30

Predicting profits from long leg of carry trade

Strategy K	r_{t-3}^{world}	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$	Δliq_{t-3}	ΔVIX_{t-3}	$term_{t-3}$	AFD_{t-3}	ΔIP_{t-3}^{OECD}
$OoS\ R^2$ (%)									
1	-0.99	6.45	1.45	1.88	-2.30	-1.24	1.25	-0.53	-3.90
2	-0.98	6.78	1.88	2.28	-2.48	-0.62	1.29	-0.41	-4.80
3	-0.82	5.28	1.61	1.17	-2.21	-0.80	1.26	-0.45	-4.19
one-sided p-values									
1	0.11	0.05	0.04	0.09	0.18	0.28	0.09	0.45	0.35
2	0.31	0.04	0.03	0.10	0.26	0.48	0.12	0.43	0.37
3	0.42	0.03	0.08	0.13	0.42	0.40	0.13	0.35	0.44

Predicting profits from long/short strategy

Strategy K	r_{t-3}^{world}	r_{t-3}^{CRB}	$\Delta\sigma_{t-3}^{equity}$	$\Delta\sigma_{t-3}^{FX}$	Δliq_{t-3}	ΔVIX_{t-3}	$term_{t-3}$	AFD_{t-3}	ΔIP_{t-3}^{OECD}
$OoS\ R^2$ (%)									
1	-1.47	6.48	1.73	3.38	-0.53	-0.73	1.03	-0.49	-3.43
2	-1.93	5.11	1.95	3.13	0.11	-1.14	1.20	-0.09	-4.66
3	-1.85	4.13	1.71	1.81	0.16	-0.85	1.16	0.01	-3.83
one-sided p-values									
1	0.16	0.04	0.03	0.02	0.16	0.31	0.08	0.14	0.35
2	0.22	0.04	0.03	0.04	0.34	0.30	0.05	0.46	0.32
3	0.32	0.03	0.07	0.08	0.31	0.43	0.05	0.36	0.35

Appendix 4.A Symmetric and asymmetric contemporaneous correlation among currency returns and the world equity index return

This table reports the contemporaneous correlations between currency returns and the world equity index return. Exchange rates are denoted as home currency per foreign currency unit (HC/FC). Thus, a positive currency return means that the foreign currency appreciates against the home currency, or the home currency depreciates against the foreign currency.

Symmetric correlations are correlations between two variables for the full sample from January 1985 to December 2011.

High-risk (low-risk) regime correlations are correlations between currency returns and negative (positive) world equity index return.

	USDGBP	USDJPY	USDCHF	USDCAD	USDAUD	USDNZD	USDNOK	USDSWK	USDEUR
Symmetric	0.28	0.17	0.13	0.46	0.42	0.38	0.33	0.39	0.26
High-risk	-0.05	-0.14	-0.08	0.37	0.30	0.36	0.13	0.18	0.03
Low-risk	0.28	0.24	0.19	0.26	0.29	0.17	0.27	0.31	0.22